RI-CLPM

Contents

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

```
load("feelings_initial.RData")
library(lavaan)
```

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

```
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
```

```r
library(tidyr)

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_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
```

- Positive inertia (0.137) and negative inertia (0.143) are about the same. Negative is slightly higher than positive.
- Arousal inertia (0.414) is much higher than the other two, meaning that arousal emotion is more likely to persist (slightly higher arousal inertia)
- All three types of emotional states (positive, negative, and arousal) exhibit significant inertia, with arousal showing the strongest carry-over effect from one trial to the next
- Ipos ~ Ineg_lag1 ($\beta = 0.166$, $p < .001$): negative emotion predicts positive emotion in the next moment, which might reflect emotional rebound
- Ineg ~ Ipos_lag1 ($\beta = 0.172$, $p < .001$): positive emotion enhances negative emotion in the next moment, which might reflect emotional mix or trial order effect
- Iaro ~ Ipos_lag1 ($\beta = -0.053$, $p < .001$): positive emotion decreases arousal at the later stage
- Iaro ~ Ineg_lag1 ($\beta = -0.078$, $p < .001$): negative emotion decreases arousal at the later stage
- Ipos ~ Iaro_lag1 ($p = 0.427$) and Ineg ~ Iaro_lag1 ($p = 0.516$) are not significant
- Conclusion:
  - **Both positive and negative emotions predict more of the opposite in the next moment**
  - **Arousal is reduced by both positive and negative emotions**
    - maybe a sign of emotional rebound or recovery
    - more likely to be a result of individual differences (some people are more responsive than others) under random trials within an experimental context, where individuals have "regression to the mean". This might not be the case in real/natural context

1.1 Difference in paths by sex

```r
# Group by sex

fit_clpm_sex <- sem(model_clpm,
                    data = clpm_data,
                    group = "sex")
```

```
## Warning: lavaan->lavParTable():
##    using a single label per parameter in a multiple group setting implies
##    imposing equality constraints across all the groups; If this is not
##    intended, either remove the label(s), or use a vector of labels (one for
##    each group); See the Multiple groups section in the man page of
##    model.syntax.
```

```r
summary(fit_clpm_sex, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 161 iterations
##
##   Estimator                                         ML
```

```
##   Optimization method                           NLMINB
##   Number of model parameters                        54
##   Number of equality constraints                    18
##
##   Number of observations per group:
##     female                                        8632
##     other                                          104
##     male                                          7488
##
## Model Test User Model:
##
##   Test statistic                                70.669
##   Degrees of freedom                                18
##   P-value (Chi-square)                           0.000
##   Test statistic for each group:
##     female                                      19.632
##     other                                       30.323
##     male                                        20.714
##
## Model Test Baseline Model:
##
##   Test statistic                             17419.660
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.997
##   Tucker-Lewis Index (TLI)                       0.994
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -102756.204
##   Loglikelihood unrestricted model (H1)    -102720.870
##
##   Akaike (AIC)                              205584.409
##   Bayesian (BIC)                            205861.402
##   Sample-size adjusted Bayesian (SABIC)     205746.996
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.023
##   90 Percent confidence interval - lower         0.018
##   90 Percent confidence interval - upper         0.029
##   P-value H_0: RMSEA <= 0.050                    1.000
##   P-value H_0: RMSEA >= 0.080                    0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.011
##
## Parameter Estimates:
##
##   Standard errors                             Standard
```

```
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
##
## Group 1 [female]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.136    0.011   12.796    0.000    0.136    0.136
##   Ineg ~
##     Ineg_lag1 (a2)    0.137    0.011   12.379    0.000    0.137    0.137
##   Iaro ~
##     Iaro_lag1 (a3)    0.408    0.009   43.375    0.000    0.408    0.413
##   Ipos ~
##     Ineg_lag1 (b1)    0.163    0.011   14.827    0.000    0.163    0.164
##     Iaro_lag1 (b2)    0.005    0.012    0.385    0.700    0.005    0.004
##   Ineg ~
##     Ipos_lag1 (c1)    0.167    0.011   15.630    0.000    0.167    0.166
##     Iaro_lag1 (c2)   -0.009    0.012   -0.705    0.481   -0.009   -0.007
##   Iaro ~
##     Ipos_lag1 (d1)   -0.045    0.008   -5.657    0.000   -0.045   -0.058
##     Ineg_lag1 (d2)   -0.065    0.008   -7.826    0.000   -0.065   -0.083
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -3.913    0.087  -44.726    0.000   -3.913   -0.549
##    .Iaro              1.264    0.058   21.802    0.000    1.264    0.241
##  .Ineg ~~
##    .Iaro              2.077    0.061   34.120    0.000    2.077    0.395
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.204    0.057   38.710    0.000    2.204    0.818
##    .Ineg              2.299    0.057   40.163    0.000    2.299    0.850
##    .Iaro              2.366    0.043   55.253    0.000    2.366    1.118
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              7.090    0.108   65.696    0.000    7.090    0.977
##    .Ineg              7.158    0.109   65.696    0.000    7.158    0.978
##    .Iaro              3.866    0.059   65.696    0.000    3.866    0.863
##
##
## Group 2 [other]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.136    0.011   12.796    0.000    0.136    0.132
##   Ineg ~
##     Ineg_lag1 (a2)    0.137    0.011   12.379    0.000    0.137    0.134
##   Iaro ~
```

```
##     Iaro_lag1 (a3)    0.408    0.009   43.375    0.000    0.408    0.356
##   Ipos ~
##     Ineg_lag1 (b1)    0.163    0.011   14.827    0.000    0.163    0.213
##     Iaro_lag1 (b2)    0.005    0.012    0.385    0.700    0.005    0.004
##   Ineg ~
##     Ipos_lag1 (c1)    0.167    0.011   15.630    0.000    0.167    0.121
##     Iaro_lag1 (c2)   -0.009    0.012   -0.705    0.481   -0.009   -0.005
##   Iaro ~
##     Ipos_lag1 (d1)   -0.045    0.008   -5.657    0.000   -0.045   -0.048
##     Ineg_lag1 (d2)   -0.065    0.008   -7.826    0.000   -0.065   -0.093
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -1.115    0.287   -3.881    0.000   -1.115   -0.412
##    .Iaro             -0.095    0.175   -0.541    0.589   -0.095   -0.053
##  .Ineg ~~
##    .Iaro              1.072    0.258    4.149    0.000    1.072    0.445
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              1.176    0.144    8.159    0.000    1.176    0.815
##    .Ineg              2.231    0.192   11.631    0.000    2.231    1.155
##    .Iaro              1.197    0.127    9.441    0.000    1.197    0.900
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.003    0.278    7.211    0.000    2.003    0.962
##    .Ineg              3.667    0.508    7.211    0.000    3.667    0.983
##    .Iaro              1.581    0.219    7.211    0.000    1.581    0.894
##
##
## Group 3 [male]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.136    0.011   12.796    0.000    0.136    0.136
##   Ineg ~
##     Ineg_lag1 (a2)    0.137    0.011   12.379    0.000    0.137    0.137
##   Iaro ~
##     Iaro_lag1 (a3)    0.408    0.009   43.375    0.000    0.408    0.402
##   Ipos ~
##     Ineg_lag1 (b1)    0.163    0.011   14.827    0.000    0.163    0.163
##     Iaro_lag1 (b2)    0.005    0.012    0.385    0.700    0.005    0.004
##   Ineg ~
##     Ipos_lag1 (c1)    0.167    0.011   15.630    0.000    0.167    0.166
##     Iaro_lag1 (c2)   -0.009    0.012   -0.705    0.481   -0.009   -0.007
##   Iaro ~
##     Ipos_lag1 (d1)   -0.045    0.008   -5.657    0.000   -0.045   -0.055
##     Ineg_lag1 (d2)   -0.065    0.008   -7.826    0.000   -0.065   -0.079
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
```

```
##   .Ipos ~~
##     .Ineg             -2.915    0.075  -38.669    0.000   -2.915   -0.500
##     .Iaro              1.155    0.054   21.448    0.000    1.155    0.256
##   .Ineg ~~
##     .Iaro              1.651    0.056   29.644    0.000    1.651    0.365
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     .Ipos              2.062    0.053   39.082    0.000    2.062    0.844
##     .Ineg              2.033    0.053   38.352    0.000    2.033    0.830
##     .Iaro              2.178    0.040   54.163    0.000    2.178    1.083
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     .Ipos              5.821    0.095   61.188    0.000    5.821    0.975
##     .Ineg              5.849    0.096   61.188    0.000    5.849    0.976
##     .Iaro              3.504    0.057   61.188    0.000    3.504    0.867
```

```
# Check for significant difference between men and women

model_clpm_free <- '
  # Inertia paths
  Ipos ~ c(a1f, a1m, a1o)*Ipos_lag1
  Ineg ~ c(a2f, a2m, a2o)*Ineg_lag1
  Iaro ~ c(a3f, a3m, a3o)*Iaro_lag1

  # Cross-lag
  Ipos ~ c(b1f, b1m, b1o)*Ineg_lag1 + c(b2f, b2m, b2o)*Iaro_lag1
  Ineg ~ c(c1f, c1m, c1o)*Ipos_lag1 + c(c2f, c2m, c2o)*Iaro_lag1
  Iaro ~ c(d1f, d1m, d1o)*Ipos_lag1 + c(d2f, d2m, d2o)*Ineg_lag1
'


fit_free <- sem(model_clpm_free, data = clpm_data, group = "sex")

# Whether there's significant difference between sex in at least one path
anova(fit_clpm_sex, fit_free)
```

```
##
## Chi-Squared Difference Test
##
##              Df    AIC    BIC  Chisq Chisq diff    RMSEA Df diff Pr(>Chisq)
## fit_free      0 205550 205965  0.000
## fit_clpm_sex 18 205584 205861 70.669     70.669 0.023261      18  3.482e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Check which paths are significantly different

lavTestScore(fit_clpm_sex)
```

```
## $test
##
```

```
## total score test:
##
##    test     X2 df p.value
## 1 score 68.394 18       0
##
## $uni
##
## univariate score tests:
##
##     lhs op   rhs     X2 df p.value
## 1  .p1. == .p28.  0.493  1   0.483
## 2  .p1. == .p55.  3.462  1   0.063
## 3  .p2. == .p29.  3.167  1   0.075
## 4  .p2. == .p56.  1.512  1   0.219
## 5  .p3. == .p30. 10.313  1   0.001
## 6  .p3. == .p57. 17.559  1   0.000
## 7  .p4. == .p31.  3.800  1   0.051
## 8  .p4. == .p58.  1.048  1   0.306
## 9  .p5. == .p32.  0.254  1   0.614
## 10 .p5. == .p59.  0.120  1   0.729
## 11 .p6. == .p33.  1.387  1   0.239
## 12 .p6. == .p60.  1.372  1   0.241
## 13 .p7. == .p34.  0.082  1   0.775
## 14 .p7. == .p61.  0.722  1   0.396
## 15 .p8. == .p35.  0.353  1   0.552
## 16 .p8. == .p62.  3.460  1   0.063
## 17 .p9. == .p36.  0.131  1   0.717
## 18 .p9. == .p63.  2.193  1   0.139
```

```r
# Understand which paths are them

pe <- parameterEstimates(fit_clpm_sex, standardized = TRUE)
pe[c(3, 30, 57), c("lhs", "op", "rhs", "group", "est", "std.all")]
```

```
##     lhs op       rhs group   est std.all
## 3  Iaro  ~ Iaro_lag1     1 0.408   0.413
## 30 Iaro  ~ Iaro_lag1     2 0.408   0.356
## 57 Iaro  ~ Iaro_lag1     3 0.408   0.402
```

- females (0.413) and males (0.402) are significantly different in arousal inertia ($p < 0.001$)
- females (0.413) and other (0.356) are also significantly different in arousal inertia ($p = 0.001$)

1.2 Difference in paths by ethnicity

```r
model_clpm_nolabel <- '
  Ipos ~ Ipos_lag1 + Ineg_lag1 + Iaro_lag1
  Ineg ~ Ineg_lag1 + Ipos_lag1 + Iaro_lag1
  Iaro ~ Iaro_lag1 + Ipos_lag1 + Ineg_lag1
'

fit_multigroup_free <- sem(model_clpm_nolabel, data = clpm_data, group = "ethn")
summary(fit_multigroup_free, standardized = TRUE)
```

```
## lavaan 0.6-19 ended normally after 343 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                       126
##
##   Number of observations per group:
##     Asian or Pacific Islander                             3536
##     Black/African American                                1456
##     Latino/Hispanic                                       1664
##     White/Caucasian                                       8112
##     Other                                                  832
##     American Indian/Native American or Alaskan Native      416
##     Decline to state                                       208
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
##   Test statistic for each group:
##     Asian or Pacific Islander                    0.000
##     Black/African American                       0.000
##     Latino/Hispanic                              0.000
##     White/Caucasian                              0.000
##     Other                                        0.000
##     American Indian/Native American or Alaskan Native    0.000
##     Decline to state                             0.000
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
##
## Group 1 [Asian or Pacific Islander]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1         0.095    0.023    4.173    0.000    0.095    0.095
##     Ineg_lag1         0.109    0.023    4.730    0.000    0.109    0.112
##     Iaro_lag1         0.028    0.026    1.088    0.277    0.028    0.023
##   Ineg ~
##     Ineg_lag1         0.143    0.023    6.096    0.000    0.143    0.143
##     Ipos_lag1         0.172    0.023    7.438    0.000    0.172    0.168
##     Iaro_lag1         0.021    0.026    0.800    0.424    0.021    0.017
##   Iaro ~
##     Iaro_lag1         0.428    0.020   21.743    0.000    0.428    0.427
##     Ipos_lag1        -0.037    0.017   -2.163    0.031   -0.037   -0.046
##     Ineg_lag1        -0.062    0.017   -3.552    0.000   -0.062   -0.078
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
```

```
##   .Ipos ~~
##     .Ineg            -3.417    0.123  -27.687    0.000   -3.417   -0.526
##     .Iaro             1.187    0.084   14.189    0.000    1.187    0.246
##   .Ineg ~~
##     .Iaro             1.771    0.088   20.117    0.000    1.771    0.360
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     .Ipos             2.334    0.110   21.223    0.000    2.334    0.918
##     .Ineg             2.090    0.112   18.646    0.000    2.090    0.801
##     .Iaro             2.134    0.083   25.587    0.000    2.134    1.026
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     .Ipos             6.371    0.152   42.048    0.000    6.371    0.986
##     .Ineg             6.619    0.157   42.048    0.000    6.619    0.972
##     .Iaro             3.665    0.087   42.048    0.000    3.665    0.847
##
##
## Group 2 [Black/African American]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    Ipos ~
##      Ipos_lag1        0.187    0.037    5.103    0.000    0.187    0.187
##      Ineg_lag1        0.192    0.039    4.939    0.000    0.192    0.191
##      Iaro_lag1       -0.107    0.043   -2.519    0.012   -0.107   -0.085
##    Ineg ~
##      Ineg_lag1        0.126    0.039    3.276    0.001    0.126    0.126
##      Ipos_lag1        0.148    0.036    4.077    0.000    0.148    0.149
##      Iaro_lag1        0.047    0.042    1.116    0.264    0.047    0.038
##    Iaro ~
##      Iaro_lag1        0.384    0.032   11.904    0.000    0.384    0.383
##      Ipos_lag1       -0.063    0.028   -2.256    0.024   -0.063   -0.079
##      Ineg_lag1       -0.070    0.029   -2.373    0.018   -0.070   -0.087
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   .Ipos ~~
##     .Ineg            -3.878    0.208  -18.626    0.000   -3.878   -0.559
##     .Iaro             1.324    0.143    9.241    0.000    1.324    0.250
##   .Ineg ~~
##     .Iaro             1.987    0.147   13.488    0.000    1.987    0.378
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     .Ipos             2.358    0.179   13.156    0.000    2.358    0.882
##     .Ineg             2.015    0.178   11.343    0.000    2.015    0.759
##     .Iaro             2.529    0.136   18.606    0.000    2.529    1.187
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     .Ipos             6.995    0.259   26.981    0.000    6.995    0.979
##     .Ineg             6.873    0.255   26.981    0.000    6.873    0.974
```

```
##    .Iaro             4.024    0.149   26.981    0.000    4.024    0.887
##
##
## Group 3 [Latino/Hispanic]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1         0.075    0.037    2.005    0.045    0.075    0.075
##     Ineg_lag1         0.103    0.038    2.718    0.007    0.103    0.103
##     Iaro_lag1         0.194    0.040    4.903    0.000    0.194    0.189
##   Ineg ~
##     Ineg_lag1         0.135    0.038    3.516    0.000    0.135    0.135
##     Ipos_lag1         0.182    0.038    4.795    0.000    0.182    0.182
##     Iaro_lag1         0.041    0.040    1.034    0.301    0.041    0.040
##   Iaro ~
##     Iaro_lag1         0.484    0.035   13.933    0.000    0.484    0.483
##     Ipos_lag1         0.034    0.033    1.032    0.302    0.034    0.035
##     Ineg_lag1         0.004    0.033    0.120    0.905    0.004    0.004
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -2.914    0.168  -17.385    0.000   -2.914   -0.471
##    .Iaro              1.895    0.139   13.610    0.000    1.895    0.354
##  .Ineg ~~
##    .Iaro              2.274    0.144   15.761    0.000    2.274    0.419
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              1.608    0.134   12.015    0.000    1.608    0.626
##    .Ineg              1.754    0.136   12.923    0.000    1.754    0.684
##    .Iaro              1.631    0.117   13.885    0.000    1.631    0.651
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              6.101    0.212   28.844    0.000    6.101    0.925
##    .Ineg              6.273    0.217   28.844    0.000    6.273    0.955
##    .Iaro              4.699    0.163   28.844    0.000    4.699    0.749
##
##
## Group 4 [White/Caucasian]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1         0.133    0.015    8.914    0.000    0.133    0.133
##     Ineg_lag1         0.179    0.016   11.465    0.000    0.179    0.177
##     Iaro_lag1        -0.014    0.018   -0.784    0.433   -0.014   -0.011
##   Ineg ~
##     Ineg_lag1         0.122    0.015    7.871    0.000    0.122    0.122
##     Ipos_lag1         0.152    0.015   10.276    0.000    0.152    0.154
##     Iaro_lag1        -0.046    0.018   -2.528    0.011   -0.046   -0.034
##   Iaro ~
```

```
##     Iaro_lag1         0.396    0.013   30.688    0.000    0.396    0.396
##     Ipos_lag1        -0.078    0.011   -7.339    0.000   -0.078   -0.104
##     Ineg_lag1        -0.090    0.011   -8.122    0.000   -0.090   -0.119
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -3.668    0.085  -42.934    0.000   -3.668   -0.542
##    .Iaro              1.130    0.055   20.450    0.000    1.130    0.233
##  .Ineg ~~
##    .Iaro              1.761    0.057   30.889    0.000    1.761    0.365
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.241    0.077   29.102    0.000    2.241    0.849
##    .Ineg              2.435    0.077   31.791    0.000    2.435    0.932
##    .Iaro              2.493    0.055   45.420    0.000    2.493    1.260
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              6.800    0.107   63.687    0.000    6.800    0.977
##    .Ineg              6.728    0.106   63.687    0.000    6.728    0.985
##    .Iaro              3.457    0.054   63.687    0.000    3.457    0.882
##
##
## Group 5 [Other]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1         0.086    0.050    1.721    0.085    0.086    0.086
##     Ineg_lag1         0.083    0.055    1.511    0.131    0.083    0.089
##     Iaro_lag1         0.094    0.062    1.530    0.126    0.094    0.078
##   Ineg ~
##     Ineg_lag1         0.223    0.058    3.812    0.000    0.223    0.222
##     Ipos_lag1         0.241    0.053    4.534    0.000    0.241    0.225
##     Iaro_lag1        -0.013    0.065   -0.204    0.838   -0.013   -0.010
##   Iaro ~
##     Iaro_lag1         0.225    0.049    4.595    0.000    0.225    0.225
##     Ipos_lag1         0.112    0.040    2.802    0.005    0.112    0.135
##     Ineg_lag1         0.072    0.044    1.647    0.099    0.072    0.093
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -3.165    0.221  -14.296    0.000   -3.165   -0.571
##    .Iaro              0.464    0.145    3.190    0.001    0.464    0.111
##  .Ineg ~~
##    .Iaro              2.278    0.172   13.219    0.000    2.278    0.516
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.175    0.229    9.483    0.000    2.175    0.940
##    .Ineg              1.885    0.243    7.755    0.000    1.885    0.760
```

```
##    .Iaro              2.331    0.183   12.760    0.000    2.331    1.216
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              5.233    0.257   20.396    0.000    5.233    0.977
##    .Ineg              5.879    0.288   20.396    0.000    5.879    0.955
##    .Iaro              3.320    0.163   20.396    0.000    3.320    0.904
##
##
## Group 6 [American Indian/Native American or Alaskan Native]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1         0.068    0.065    1.045    0.296    0.068    0.068
##     Ineg_lag1         0.089    0.061    1.456    0.145    0.089    0.112
##     Iaro_lag1        -0.131    0.072   -1.816    0.069   -0.131   -0.130
##   Ineg ~
##     Ineg_lag1         0.214    0.077    2.796    0.005    0.214    0.212
##     Ipos_lag1         0.177    0.081    2.178    0.029    0.177    0.140
##     Iaro_lag1        -0.013    0.090   -0.144    0.886   -0.013   -0.010
##   Iaro ~
##     Iaro_lag1         0.008    0.072    0.108    0.914    0.008    0.008
##     Ipos_lag1         0.125    0.065    1.919    0.055    0.125    0.124
##     Ineg_lag1         0.127    0.061    2.084    0.037    0.127    0.159
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -1.208    0.152   -7.928    0.000   -1.208   -0.422
##    .Iaro              0.473    0.114    4.134    0.000    0.473    0.207
##  .Ineg ~~
##    .Iaro              1.578    0.160    9.840    0.000    1.578    0.551
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              1.975    0.189   10.472    0.000    1.975    1.302
##    .Ineg              1.486    0.236    6.288    0.000    1.486    0.770
##    .Iaro              1.681    0.189    8.904    0.000    1.681    1.097
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.284    0.158   14.422    0.000    2.284    0.992
##    .Ineg              3.587    0.249   14.422    0.000    3.587    0.963
##    .Iaro              2.287    0.159   14.422    0.000    2.287    0.974
##
##
## Group 7 [Decline to state]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1         0.050    0.100    0.507    0.612    0.050    0.050
##     Ineg_lag1         0.051    0.111    0.460    0.645    0.051    0.050
```

```
##     Iaro_lag1         0.123    0.114    1.075    0.282    0.123    0.116
##   Ineg ~
##     Ineg_lag1         0.143    0.108    1.322    0.186    0.143    0.144
##     Ipos_lag1         0.196    0.098    2.010    0.044    0.196    0.199
##     Iaro_lag1        -0.006    0.112   -0.049    0.961   -0.006   -0.005
##   Iaro ~
##     Iaro_lag1         0.286    0.105    2.725    0.006    0.286    0.286
##     Ipos_lag1         0.027    0.091    0.300    0.764    0.027    0.029
##     Ineg_lag1        -0.030    0.102   -0.300    0.764   -0.030   -0.032
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -1.966    0.363   -5.410    0.000   -1.966   -0.405
##    .Iaro              1.453    0.331    4.391    0.000    1.453    0.320
##  .Ineg ~~
##    .Iaro              2.285    0.347    6.577    0.000    2.285    0.512
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              1.949    0.360    5.413    0.000    1.949    0.864
##    .Ineg              1.784    0.353    5.050    0.000    1.784    0.801
##    .Iaro              2.242    0.330    6.784    0.000    2.242    1.052
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              4.953    0.486   10.198    0.000    4.953    0.973
##    .Ineg              4.766    0.467   10.198    0.000    4.766    0.962
##    .Iaro              4.173    0.409   10.198    0.000    4.173    0.919
```

- Asian or Pacific Islander:
  - strong arousal inertia (β = .43, p < .001).
  - Both prior positive (β = −.05, p = .031) and negative emotion (β = −.08, p < .001) significantly reduced subsequent arousal
- Black/African American:
  - Strongest Ipos inertia (β = .187) among all groups (p < .001)
  - Arousal -> Positive emotion path is negative and significant (β=-.085, p = .012), suggesting arousal suppresses positivity here
- Latino/Hispanic:
  - Uniquely positive effect from prior arousal to later positive emotion (β = .189, p < .001).
  - Had the strongest Iaro inertia (β = .483, p < .001).
- White/Caucasian:
  - Negative cross-effects from both Ipos to Iaro (β = -.104, p < .001) and Ineg to Iaro (β = -.119, p < .001), showing a strong regulatory suppression of arousal by both emotion valences.
  - Effects tend to be more stable across emotional domains.
- American Indian/Native American or Alaskan Native:
  - The highest negative emotion inertia (β = .21, p = .005)
  - The only group where prior negative emotion significantly increased arousal (β = .16, p = .037)

1.3 Difference in paths by age

```r
library(dplyr)
library(broom)

# cross-lagged paths to analyze
paths <- list(
  Ipos_on_Ineg = c("Ipos", "Ineg_lag1"),
  Ipos_on_Aro = c("Ipos", "Iaro_lag1"),
  Ineg_on_Ipos = c("Ineg", "Ipos_lag1"),
  Ineg_on_Aro = c("Ineg", "Iaro_lag1"),
  Iaro_on_Ipos = c("Iaro", "Ipos_lag1"),
  Iaro_on_Ineg = c("Iaro", "Ineg_lag1")
)

results <- data.frame(path = character(), r = numeric(), p = numeric())

# run regression for each path + correlation with age
for (path_name in names(paths)) {
  lhs <- paths[[path_name]][1]
  rhs <- paths[[path_name]][2]

  # model each participant
  path_df <- clpm_data %>%
    group_by(subj) %>%
    filter(!is.na(.data[[lhs]]), !is.na(.data[[rhs]])) %>%
    do(tidy(lm(as.formula(paste(lhs, "~", rhs)), data = .))) %>%
    filter(term == rhs) %>%
    rename(estimate = estimate) %>%
    left_join(select(dat, subj, age), by = "subj")

  # find correlation with age
  cor_result <- cor.test(path_df$estimate, path_df$age)

  results <- rbind(results, data.frame(
    path = path_name,
    r = cor_result$estimate,
    p = cor_result$p.value
  ))
}

print(results)
```

```
##              path            r             p
## cor  Ipos_on_Ineg  0.124382721  1.763779e-57
## cor1  Ipos_on_Aro  0.202148879 1.272849e-150
## cor2 Ineg_on_Ipos -0.029140986  1.914050e-04
## cor3  Ineg_on_Aro -0.215376975 3.457817e-171
## cor4 Iaro_on_Ipos  0.009095577  2.444131e-01
## cor5 Iaro_on_Ineg -0.037882643  1.236128e-06
```

- Ipos_on_Ineg: As age increases, negative emotion exerts a stronger influence on subsequent positive emotion ($r = 0.124$, $p < .001$)

- Ipos_on_Aro: Higher arousal increasingly boosts next-step positive emotion with greater age ($r = 0.202$, $p < .001$)
- Ineg_on_Aro: Higher arousal is linked with lower next-step negative emotion, especially as age increases ($r = -0.215$, $p < .001$)
- Iaro_on_Ineg: With age, the influence of negative emotion on subsequent arousal slightly decreases ($r = -0.038$, $p < .001$)

2 RI-CLPM (Random-Intercept)–Causality

```
# ---------------------------------------------------------------------------------
# EXAMPLE 1: RI-CLPM FOR THREE TIME POINTS (t=1,2,3)
# We use the original `dat` (not filtered `clpm_data`) to ensure time 1 is included.
# ---------------------------------------------------------------------------------

# 1) Reshape the data to wide format for trials 1-3
wide3 <- dat %>%
  # Keep only trials 1, 2, and 3
  filter(trial.num %in% 1:3) %>%
  # Select subject ID plus the three emotion measures with their trial index
  select(subj, trial.num, Ipos, Ineg, Iaro) %>%
  # Pivot wide: one row per subject, columns Ipos_t1, Ipos_t2, Ipos_t3, etc.
  pivot_wider(
    id_cols      = subj,
    names_from   = trial.num,
    names_prefix = "t",
    values_from  = c(Ipos, Ineg, Iaro)
  )

# Check that wide3 contains the expected columns:
colnames(wide3)
```

```
##  [1] "subj"    "Ipos_t1" "Ipos_t2" "Ipos_t3" "Ineg_t1" "Ineg_t2" "Ineg_t3"
##  [8] "Iaro_t1" "Iaro_t2" "Iaro_t3"
```

```
# Expected: subj, Ipos_t1, Ipos_t2, Ipos_t3, Ineg_t1, ..., Iaro_t3
```

```
# 2) Define the RI-CLPM model syntax
library(lavaan)
model_riclpm_3 <- '

  # 2.1 Random intercept (trait) latent factors:
  #     Each RI factor loads with coefficient = 1 on its observed indicators
  #     to capture stable between-person differences across t1-t3.
  RIpos =~ 1*Ipos_t1 + 1*Ipos_t2 + 1*Ipos_t3
  RIneg =~ 1*Ineg_t1 + 1*Ineg_t2 + 1*Ineg_t3
  RIaro =~ 1*Iaro_t1 + 1*Iaro_t2 + 1*Iaro_t3

  # 2.2 De-mean observed variables (fix intercepts to zero):
  #     Ensures residuals reflect within-person deviations from each person's mean.
  Ipos_t1 ~ 0*1
```

```
  Ipos_t2 ~ 0*1
  Ipos_t3 ~ 0*1
  Ineg_t1 ~ 0*1
  Ineg_t2 ~ 0*1
  Ineg_t3 ~ 0*1
  Iaro_t1 ~ 0*1
  Iaro_t2 ~ 0*1
  Iaro_t3 ~ 0*1

  # 2.3 Constrain residuals and RIs to be uncorrelated:
  #     Isolates within-person (state) variance from between-person (trait) variance.

  Ipos_t1 ~~ 0*RIpos
  Ipos_t2 ~~ 0*RIpos
  Ipos_t3 ~~ 0*RIpos
  Ineg_t1 ~~ 0*RIneg
  Ineg_t2 ~~ 0*RIneg
  Ineg_t3 ~~ 0*RIneg
  Iaro_t1 ~~ 0*RIaro
  Iaro_t2 ~~ 0*RIaro
  Iaro_t3 ~~ 0*RIaro

  # 2.4 Within-person lagged effects (on the residual/state level):
  #     Autoregressive ("inertia") and cross-lagged paths for t2 and t3.
  #   At time 2:
  Ipos_t2 ~ a1*Ipos_t1 + b1*Ineg_t1 + b2*Iaro_t1
  Ineg_t2 ~ a2*Ineg_t1 + c1*Ipos_t1 + c2*Iaro_t1
  Iaro_t2 ~ a3*Iaro_t1 + d1*Ipos_t1 + d2*Ineg_t1

  #   At time 3:
  Ipos_t3 ~ a1*Ipos_t2 + b1*Ineg_t2 + b2*Iaro_t2
  Ineg_t3 ~ a2*Ineg_t2 + c1*Ipos_t2 + c2*Iaro_t2
  Iaro_t3 ~ a3*Iaro_t2 + d1*Ipos_t2 + d2*Ineg_t2
'

# 3) Fit the RI-CLPM with MLR estimator (robust ML)
fit_riclpm_3 <- sem(
  model     = model_riclpm_3,
  data      = wide3,
  estimator = "MLR"
)
```

```
## Warning: lavaan->lav_object_post_check():
##    covariance matrix of latent variables is not positive definite ; use
##    lavInspect(fit, "cov.lv") to investigate.
```

```
# 4) Summarize results with standardized estimates and fit indices
summary(fit_riclpm_3, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 99 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
```

```
##   Number of model parameters                        33
##   Number of equality constraints                     9
##
##   Number of observations                           156
##
## Model Test User Model:
##                                               Standard      Scaled
##   Test Statistic                               472.096     450.676
##   Degrees of freedom                                30          30
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  1.048
##     Yuan-Bentler correction (Mplus variant)
##
## Model Test Baseline Model:
##
##   Test statistic                               481.779     390.692
##   Degrees of freedom                                36          36
##   P-value                                        0.000       0.000
##   Scaling correction factor                                  1.233
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.008       0.000
##   Tucker-Lewis Index (TLI)                      -0.190      -0.423
##
##   Robust Comparative Fit Index (CFI)                         0.000
##   Robust Tucker-Lewis Index (TLI)                           -0.209
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -3163.339   -3163.339
##   Scaling correction factor                                  0.892
##       for the MLR correction
##   Loglikelihood unrestricted model (H1)      -2927.291   -2927.291
##   Scaling correction factor                                  1.127
##       for the MLR correction
##
##   Akaike (AIC)                                6374.678    6374.678
##   Bayesian (BIC)                              6447.875    6447.875
##   Sample-size adjusted Bayesian (SABIC)       6371.907    6371.907
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.307       0.300
##   90 Percent confidence interval - lower         0.283       0.276
##   90 Percent confidence interval - upper         0.332       0.324
##   P-value H_0: RMSEA <= 0.050                    0.000       0.000
##   P-value H_0: RMSEA >= 0.080                    1.000       1.000
##
##   Robust RMSEA                                               0.307
##   90 Percent confidence interval - lower                     0.282
##   90 Percent confidence interval - upper                     0.332
##   P-value H_0: Robust RMSEA <= 0.050                         0.000
##   P-value H_0: Robust RMSEA >= 0.080                         1.000
```

```
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                          1.752       1.752
##
## Parameter Estimates:
##
##   Standard errors                             Sandwich
##   Information bread                           Observed
##   Observed information based on                Hessian
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   RIpos =~
##     Ipos_t1           1.000                               2.958    0.782
##     Ipos_t2           1.000                               2.958    0.753
##     Ipos_t3           1.000                               2.958    0.737
##   RIneg =~
##     Ineg_t1           1.000                               2.337    0.670
##     Ineg_t2           1.000                               2.337    0.623
##     Ineg_t3           1.000                               2.337    0.599
##   RIaro =~
##     Iaro_t1           1.000                               3.778    0.945
##     Iaro_t2           1.000                               3.778    1.017
##     Iaro_t3           1.000                               3.778    0.952
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos_t2 ~
##     Ipos_t1   (a1)    0.359    0.110    3.279    0.001    0.359    0.346
##     Ineg_t1   (b1)    0.661    0.099    6.678    0.000    0.661    0.586
##     Iaro_t1   (b2)   -0.752    0.154   -4.890    0.000   -0.752   -0.765
##   Ineg_t2 ~
##     Ineg_t1   (a2)    0.717    0.133    5.377    0.000    0.717    0.666
##     Ipos_t1   (c1)    0.782    0.082    9.591    0.000    0.782    0.789
##     Iaro_t1   (c2)   -1.079    0.127   -8.494    0.000   -1.079   -1.150
##   Iaro_t2 ~
##     Iaro_t1   (a3)   -0.003    0.094   -0.033    0.974   -0.003   -0.003
##     Ipos_t1   (d1)   -0.020    0.061   -0.325    0.745   -0.020   -0.020
##     Ineg_t1   (d2)   -0.093    0.063   -1.462    0.144   -0.093   -0.087
##   Ipos_t3 ~
##     Ipos_t2   (a1)    0.359    0.110    3.279    0.001    0.359    0.351
##     Ineg_t2   (b1)    0.661    0.099    6.678    0.000    0.661    0.617
##     Iaro_t2   (b2)   -0.752    0.154   -4.890    0.000   -0.752   -0.696
##   Ineg_t3 ~
##     Ineg_t2   (a2)    0.717    0.133    5.377    0.000    0.717    0.690
##     Ipos_t2   (c1)    0.782    0.082    9.591    0.000    0.782    0.787
##     Iaro_t2   (c2)   -1.079    0.127   -8.494    0.000   -1.079   -1.028
##   Iaro_t3 ~
##     Iaro_t2   (a3)   -0.003    0.094   -0.033    0.974   -0.003   -0.003
##     Ipos_t2   (d1)   -0.020    0.061   -0.325    0.745   -0.020   -0.020
##     Ineg_t2   (d2)   -0.093    0.063   -1.462    0.144   -0.093   -0.088
##
## Covariances:
```

```
##                     Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   RIpos ~~
##    .Ipos_t1           0.000                                0.000    0.000
##    .Ipos_t2           0.000                                0.000    0.000
##    .Ipos_t3           0.000                                0.000    0.000
##   RIneg ~~
##    .Ineg_t1           0.000                                0.000    0.000
##    .Ineg_t2           0.000                                0.000    0.000
##    .Ineg_t3           0.000                                0.000    0.000
##   RIaro ~~
##    .Iaro_t1           0.000                                0.000    0.000
##    .Iaro_t2           0.000                                0.000    0.000
##    .Iaro_t3           0.000                                0.000    0.000
##   RIpos ~~
##     RIneg             6.133    0.569   10.780    0.000    0.887    0.887
##     RIaro            11.413    1.092   10.452    0.000    1.021    1.021
##   RIneg ~~
##     RIaro            10.081    1.107    9.108    0.000    1.142    1.142
##
## Intercepts:
##                     Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos_t1           0.000                                0.000    0.000
##    .Ipos_t2           0.000                                0.000    0.000
##    .Ipos_t3           0.000                                0.000    0.000
##    .Ineg_t1           0.000                                0.000    0.000
##    .Ineg_t2           0.000                                0.000    0.000
##    .Ineg_t3           0.000                                0.000    0.000
##    .Iaro_t1           0.000                                0.000    0.000
##    .Iaro_t2           0.000                                0.000    0.000
##    .Iaro_t3           0.000                                0.000    0.000
##
## Variances:
##                     Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos_t1           5.569    0.749    7.435    0.000    5.569    0.389
##    .Ipos_t2           6.531    0.856    7.631    0.000    6.531    0.423
##    .Ipos_t3           7.555    1.060    7.128    0.000    7.555    0.469
##    .Ineg_t1           6.692    0.899    7.445    0.000    6.692    0.551
##    .Ineg_t2           7.315    0.890    8.221    0.000    7.315    0.520
##    .Ineg_t3          10.772    1.537    7.007    0.000   10.772    0.708
##    .Iaro_t1           1.712    0.231    7.412    0.000    1.712    0.107
##    .Iaro_t2           1.803    0.239    7.542    0.000    1.803    0.131
##    .Iaro_t3           3.862    0.513    7.522    0.000    3.862    0.245
##     RIpos             8.750    1.386    6.315    0.000    1.000    1.000
##     RIneg             5.461    1.353    4.038    0.000    1.000    1.000
##     RIaro            14.270    1.378   10.357    0.000    1.000    1.000
```

```
# ------------------------------------------------------------------------------------
# EXAMPLE 2: BLOCK-BASED RI-CLPM (AVERAGE EVERY 10 TRIALS → 11 BLOCKS)
# Aggregates high-frequency data to improve model identification.
# ------------------------------------------------------------------------------------

# 1) Create block variable (1-11) and compute block-wise averages per subject

block_size <- 10
```

```r
clpm_block <- dat %>%
  # Assign each trial to a block index (e.g., trial 1-10 → block 1, etc.)
  mutate(block = ceiling(trial.num / block_size)) %>%
  # Group by subject and block
  group_by(subj, block) %>%
  # Compute mean Ipos, Ineg, Iaro within each block
  summarise(
    Ipos = mean(Ipos),
    Ineg = mean(Ineg),
    Iaro = mean(Iaro),
    .groups = "drop"
  )

# 2) Pivot the block-level data to wide format: Ipos_b1, Ipos_b2, ..., Iaro_b11
wide_blk <- clpm_block %>%
  pivot_wider(
    id_cols      = subj,
    names_from   = block,
    names_prefix = "b",
    values_from  = c(Ipos, Ineg, Iaro)
  )

# 3) Dynamically build the RI-CLPM syntax for 11 blocks

# Identify block indices and variable names
waves <- sort(unique(clpm_block$block))  # 1:11
vars  <- c("Ipos","Ineg","Iaro")
vc    <- sub("^I", "", vars)             # Clean names: "pos","neg","aro"

# 3.1 Trait factors: each RI loads equally (1*) on all blocks
trait <- sapply(seq_along(vars), function(i){
  paste0("RI", vc[i], " =~ ",
         paste0("1*", vars[i], "_b", waves, collapse=" + "))
})

# 3.2 De-mean by fixing intercepts of all observed block scores to zero
ints <- unlist(lapply(vars, function(v){
  paste0(v, "_b", waves, " ~ 0*1")
}))

# 3.3 Constrain residuals of observed blocks to be uncorrelated with their RI
nocov <- unlist(lapply(vc, function(x){
  paste0("I", x, "_b", waves, " ~~ 0*RI", x)
}))

# 3.4 Specify within-person lagged regression paths for blocks 2-11
lags <- unlist(lapply(waves[-1], function(w){
  w0 <- w-1
  c(
    sprintf("Ipos_b%d ~ a1*Ipos_b%d + b1*Ineg_b%d + b2*Iaro_b%d", w, w0, w0, w0),
    sprintf("Ineg_b%d ~ a2*Ineg_b%d + c1*Ipos_b%d + c2*Iaro_b%d", w, w0, w0, w0),
    sprintf("Iaro_b%d ~ a3*Iaro_b%d + d1*Ipos_b%d + d2*Ineg_b%d", w, w0, w0, w0)
  )
```

```r
}))

# 3.5 Combine all parts-each line separated by a newline-for lavaan
model_blk_riclpm <- paste(c(trait, ints, nocov, lags), collapse="\n")

# 4) Fit the block-based RI-CLPM
fit_blk_riclpm <- sem(
  model     = model_blk_riclpm,
  data      = wide_blk,
  estimator = "MLR"
)

# 5) Output summary with standardized estimates and fit indices
summary(fit_blk_riclpm, standardized=TRUE, fit.measures=TRUE)
```

```
## lavaan 0.6-19 ended normally after 77 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                       129
##   Number of equality constraints                    81
##
##   Number of observations                           156
##
## Model Test User Model:
##                                               Standard      Scaled
##   Test Statistic                              2309.705    2096.792
##   Degrees of freedom                               546         546
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  1.102
##     Yuan-Bentler correction (Mplus variant)
##
## Model Test Baseline Model:
##
##   Test statistic                              6881.327    6031.157
##   Degrees of freedom                               528         528
##   P-value                                        0.000       0.000
##   Scaling correction factor                                  1.141
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.722       0.718
##   Tucker-Lewis Index (TLI)                       0.732       0.727
##
##   Robust Comparative Fit Index (CFI)                         0.728
##   Robust Tucker-Lewis Index (TLI)                            0.737
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -5585.941   -5585.941
##   Scaling correction factor                                  0.497
##       for the MLR correction
##   Loglikelihood unrestricted model (H1)      -4431.089   -4431.089
```

```
##   Scaling correction factor                                  1.121
##       for the MLR correction
##
##   Akaike (AIC)                              11267.882   11267.882
##   Bayesian (BIC)                            11414.275   11414.275
##   Sample-size adjusted Bayesian (SABIC)     11262.340   11262.340
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                         0.144       0.135
##   90 Percent confidence interval - lower        0.138       0.129
##   90 Percent confidence interval - upper        0.150       0.141
##   P-value H_0: RMSEA <= 0.050                   0.000       0.000
##   P-value H_0: RMSEA >= 0.080                   1.000       1.000
##
##   Robust RMSEA                                              0.142
##   90 Percent confidence interval - lower                    0.135
##   90 Percent confidence interval - upper                    0.148
##   P-value H_0: Robust RMSEA <= 0.050                        0.000
##   P-value H_0: Robust RMSEA >= 0.080                        1.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                          7.949       7.949
##
## Parameter Estimates:
##
##   Standard errors                             Sandwich
##   Information bread                           Observed
##   Observed information based on                Hessian
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   RIpos =~
##     Ipos_b1           1.000                                3.170    0.983
##     Ipos_b2           1.000                                3.170    0.994
##     Ipos_b3           1.000                                3.170    0.990
##     Ipos_b4           1.000                                3.170    0.981
##     Ipos_b5           1.000                                3.170    0.977
##     Ipos_b6           1.000                                3.170    0.985
##     Ipos_b7           1.000                                3.170    0.985
##     Ipos_b8           1.000                                3.170    0.977
##     Ipos_b9           1.000                                3.170    0.990
##     Ipos_b10          1.000                                3.170    0.983
##     Ipos_b11          1.000                                3.170    0.969
##   RIneg =~
##     Ineg_b1           1.000                                3.071    0.980
##     Ineg_b2           1.000                                3.071    0.943
##     Ineg_b3           1.000                                3.071    0.958
##     Ineg_b4           1.000                                3.071    0.946
##     Ineg_b5           1.000                                3.071    0.947
##     Ineg_b6           1.000                                3.071    0.949
##     Ineg_b7           1.000                                3.071    0.950
##     Ineg_b8           1.000                                3.071    0.947
```

```
##     Ineg_b9           1.000                               3.071    0.952
##     Ineg_b10          1.000                               3.071    0.945
##     Ineg_b11          1.000                               3.071    0.926
##   RIaro =~
##     Iaro_b1           1.000                               3.570    0.989
##     Iaro_b2           1.000                               3.570    1.008
##     Iaro_b3           1.000                               3.570    1.011
##     Iaro_b4           1.000                               3.570    1.015
##     Iaro_b5           1.000                               3.570    1.014
##     Iaro_b6           1.000                               3.570    1.014
##     Iaro_b7           1.000                               3.570    1.012
##     Iaro_b8           1.000                               3.570    1.012
##     Iaro_b9           1.000                               3.570    1.011
##     Iaro_b10          1.000                               3.570    1.010
##     Iaro_b11          1.000                               3.570    1.001
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos_b2 ~
##     Ipos_b1   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.105
##     Ineg_b1   (b1)    0.239    0.028    8.662    0.000    0.239    0.235
##     Iaro_b1   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.148
##   Ineg_b2 ~
##     Ineg_b1   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.107
##     Ipos_b1   (c1)    0.252    0.023   11.154    0.000    0.252    0.250
##     Iaro_b1   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.110
##   Iaro_b2 ~
##     Iaro_b1   (a3)    0.145    0.043    3.363    0.001    0.145    0.148
##     Ipos_b1   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.056
##     Ineg_b1   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.117
##   Ipos_b3 ~
##     Ipos_b2   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.103
##     Ineg_b2   (b1)    0.239    0.028    8.662    0.000    0.239    0.243
##     Iaro_b2   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.145
##   Ineg_b3 ~
##     Ineg_b2   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.113
##     Ipos_b2   (c1)    0.252    0.023   11.154    0.000    0.252    0.251
##     Iaro_b2   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.110
##   Iaro_b3 ~
##     Iaro_b2   (a3)    0.145    0.043    3.363    0.001    0.145    0.146
##     Ipos_b2   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.056
##     Ineg_b2   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.122
##   Ipos_b4 ~
##     Ipos_b3   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.103
##     Ineg_b3   (b1)    0.239    0.028    8.662    0.000    0.239    0.237
##     Iaro_b3   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.143
##   Ineg_b4 ~
##     Ineg_b3   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.110
##     Ipos_b3   (c1)    0.252    0.023   11.154    0.000    0.252    0.249
##     Iaro_b3   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.108
##   Iaro_b4 ~
##     Iaro_b3   (a3)    0.145    0.043    3.363    0.001    0.145    0.146
##     Ipos_b3   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.056
##     Ineg_b3   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.120
```

```
##   Ipos_b5 ~
##     Ipos_b4   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.103
##     Ineg_b4   (b1)    0.239    0.028    8.662    0.000    0.239    0.239
##     Iaro_b4   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.142
##   Ineg_b5 ~
##     Ineg_b4   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.112
##     Ipos_b4   (c1)    0.252    0.023   11.154    0.000    0.252    0.251
##     Iaro_b4   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.108
##   Iaro_b5 ~
##     Iaro_b4   (a3)    0.145    0.043    3.363    0.001    0.145    0.145
##     Ipos_b4   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.057
##     Ineg_b4   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.122
##   Ipos_b6 ~
##     Ipos_b5   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.105
##     Ineg_b5   (b1)    0.239    0.028    8.662    0.000    0.239    0.241
##     Iaro_b5   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.143
##   Ineg_b6 ~
##     Ineg_b5   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.112
##     Ipos_b5   (c1)    0.252    0.023   11.154    0.000    0.252    0.253
##     Iaro_b5   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.108
##   Iaro_b6 ~
##     Iaro_b5   (a3)    0.145    0.043    3.363    0.001    0.145    0.145
##     Ipos_b5   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.057
##     Ineg_b5   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.121
##   Ipos_b7 ~
##     Ipos_b6   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.104
##     Ineg_b6   (b1)    0.239    0.028    8.662    0.000    0.239    0.240
##     Iaro_b6   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.143
##   Ineg_b7 ~
##     Ineg_b6   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.112
##     Ipos_b6   (c1)    0.252    0.023   11.154    0.000    0.252    0.251
##     Iaro_b6   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.108
##   Iaro_b7 ~
##     Iaro_b6   (a3)    0.145    0.043    3.363    0.001    0.145    0.145
##     Ipos_b6   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.057
##     Ineg_b6   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.121
##   Ipos_b8 ~
##     Ipos_b7   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.103
##     Ineg_b7   (b1)    0.239    0.028    8.662    0.000    0.239    0.238
##     Iaro_b7   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.142
##   Ineg_b8 ~
##     Ineg_b7   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.111
##     Ipos_b7   (c1)    0.252    0.023   11.154    0.000    0.252    0.250
##     Iaro_b7   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.108
##   Iaro_b8 ~
##     Iaro_b7   (a3)    0.145    0.043    3.363    0.001    0.145    0.145
##     Ipos_b7   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.057
##     Ineg_b7   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.121
##   Ipos_b9 ~
##     Ipos_b8   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.105
##     Ineg_b8   (b1)    0.239    0.028    8.662    0.000    0.239    0.242
##     Iaro_b8   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.144
##   Ineg_b9 ~
##     Ineg_b8   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.112
```

```
##     Ipos_b8   (c1)    0.252    0.023   11.154    0.000    0.252    0.254
##     Iaro_b8   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.109
##   Iaro_b9 ~
##     Iaro_b8   (a3)    0.145    0.043    3.363    0.001    0.145    0.145
##     Ipos_b8   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.057
##     Ineg_b8   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.121
##   Ipos_b10 ~
##     Ipos_b9   (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.103
##     Ineg_b9   (b1)    0.239    0.028    8.662    0.000    0.239    0.239
##     Iaro_b9   (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.143
##   Ineg_b10 ~
##     Ineg_b9   (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.111
##     Ipos_b9   (c1)    0.252    0.023   11.154    0.000    0.252    0.248
##     Iaro_b9   (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.108
##   Iaro_b10 ~
##     Iaro_b9   (a3)    0.145    0.043    3.363    0.001    0.145    0.145
##     Ipos_b9   (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.056
##     Ineg_b9   (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.120
##   Ipos_b11 ~
##     Ipos_b10  (a1)   -0.104    0.028   -3.664    0.000   -0.104   -0.102
##     Ineg_b10  (b1)    0.239    0.028    8.662    0.000    0.239    0.238
##     Iaro_b10  (b2)   -0.131    0.036   -3.617    0.000   -0.131   -0.142
##   Ineg_b11 ~
##     Ineg_b10  (a2)   -0.112    0.027   -4.068    0.000   -0.112   -0.109
##     Ipos_b10  (c1)    0.252    0.023   11.154    0.000    0.252    0.245
##     Iaro_b10  (c2)   -0.099    0.033   -3.031    0.002   -0.099   -0.106
##   Iaro_b11 ~
##     Iaro_b10  (a3)    0.145    0.043    3.363    0.001    0.145    0.144
##     Ipos_b10  (d1)   -0.062    0.026   -2.383    0.017   -0.062   -0.056
##     Ineg_b10  (d2)   -0.132    0.032   -4.130    0.000   -0.132   -0.120
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   RIpos ~~
##    .Ipos_b1           0.000                               0.000    0.000
##    .Ipos_b2           0.000                               0.000    0.000
##    .Ipos_b3           0.000                               0.000    0.000
##    .Ipos_b4           0.000                               0.000    0.000
##    .Ipos_b5           0.000                               0.000    0.000
##    .Ipos_b6           0.000                               0.000    0.000
##    .Ipos_b7           0.000                               0.000    0.000
##    .Ipos_b8           0.000                               0.000    0.000
##    .Ipos_b9           0.000                               0.000    0.000
##    .Ipos_b10          0.000                               0.000    0.000
##    .Ipos_b11          0.000                               0.000    0.000
##   RIneg ~~
##    .Ineg_b1           0.000                               0.000    0.000
##    .Ineg_b2           0.000                               0.000    0.000
##    .Ineg_b3           0.000                               0.000    0.000
##    .Ineg_b4           0.000                               0.000    0.000
##    .Ineg_b5           0.000                               0.000    0.000
##    .Ineg_b6           0.000                               0.000    0.000
##    .Ineg_b7           0.000                               0.000    0.000
##    .Ineg_b8           0.000                               0.000    0.000
```

```
##    .Ineg_b9           0.000                               0.000    0.000
##    .Ineg_b10          0.000                               0.000    0.000
##    .Ineg_b11          0.000                               0.000    0.000
##   RIaro ~~
##    .Iaro_b1           0.000                               0.000    0.000
##    .Iaro_b2           0.000                               0.000    0.000
##    .Iaro_b3           0.000                               0.000    0.000
##    .Iaro_b4           0.000                               0.000    0.000
##    .Iaro_b5           0.000                               0.000    0.000
##    .Iaro_b6           0.000                               0.000    0.000
##    .Iaro_b7           0.000                               0.000    0.000
##    .Iaro_b8           0.000                               0.000    0.000
##    .Iaro_b9           0.000                               0.000    0.000
##    .Iaro_b10          0.000                               0.000    0.000
##    .Iaro_b11          0.000                               0.000    0.000
##   RIpos ~~
##     RIneg            9.583    0.394   24.352    0.000    0.984    0.984
##     RIaro           11.043    0.561   19.671    0.000    0.976    0.976
##   RIneg ~~
##     RIaro           10.689    0.524   20.391    0.000    0.975    0.975
##
## Intercepts:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos_b1           0.000                               0.000    0.000
##    .Ipos_b2           0.000                               0.000    0.000
##    .Ipos_b3           0.000                               0.000    0.000
##    .Ipos_b4           0.000                               0.000    0.000
##    .Ipos_b5           0.000                               0.000    0.000
##    .Ipos_b6           0.000                               0.000    0.000
##    .Ipos_b7           0.000                               0.000    0.000
##    .Ipos_b8           0.000                               0.000    0.000
##    .Ipos_b9           0.000                               0.000    0.000
##    .Ipos_b10          0.000                               0.000    0.000
##    .Ipos_b11          0.000                               0.000    0.000
##    .Ineg_b1           0.000                               0.000    0.000
##    .Ineg_b2           0.000                               0.000    0.000
##    .Ineg_b3           0.000                               0.000    0.000
##    .Ineg_b4           0.000                               0.000    0.000
##    .Ineg_b5           0.000                               0.000    0.000
##    .Ineg_b6           0.000                               0.000    0.000
##    .Ineg_b7           0.000                               0.000    0.000
##    .Ineg_b8           0.000                               0.000    0.000
##    .Ineg_b9           0.000                               0.000    0.000
##    .Ineg_b10          0.000                               0.000    0.000
##    .Ineg_b11          0.000                               0.000    0.000
##    .Iaro_b1           0.000                               0.000    0.000
##    .Iaro_b2           0.000                               0.000    0.000
##    .Iaro_b3           0.000                               0.000    0.000
##    .Iaro_b4           0.000                               0.000    0.000
##    .Iaro_b5           0.000                               0.000    0.000
##    .Iaro_b6           0.000                               0.000    0.000
##    .Iaro_b7           0.000                               0.000    0.000
##    .Iaro_b8           0.000                               0.000    0.000
##    .Iaro_b9           0.000                               0.000    0.000
```

```
##     .Iaro_b10          0.000                               0.000    0.000
##     .Iaro_b11          0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     .Ipos_b1           0.359    0.049    7.391    0.000    0.359    0.034
##     .Ipos_b2           0.473    0.060    7.897    0.000    0.473    0.046
##     .Ipos_b3           0.257    0.043    5.993    0.000    0.257    0.025
##     .Ipos_b4           0.489    0.072    6.789    0.000    0.489    0.047
##     .Ipos_b5           0.545    0.066    8.250    0.000    0.545    0.052
##     .Ipos_b6           0.375    0.065    5.810    0.000    0.375    0.036
##     .Ipos_b7           0.381    0.055    6.904    0.000    0.381    0.037
##     .Ipos_b8           0.549    0.065    8.492    0.000    0.549    0.052
##     .Ipos_b9           0.253    0.035    7.231    0.000    0.253    0.025
##     .Ipos_b10          0.412    0.060    6.823    0.000    0.412    0.040
##     .Ipos_b11          0.706    0.109    6.487    0.000    0.706    0.066
##     .Ineg_b1           0.394    0.060    6.536    0.000    0.394    0.040
##     .Ineg_b2           0.510    0.074    6.933    0.000    0.510    0.048
##     .Ineg_b3           0.255    0.034    7.613    0.000    0.255    0.025
##     .Ineg_b4           0.446    0.055    8.170    0.000    0.446    0.042
##     .Ineg_b5           0.432    0.057    7.581    0.000    0.432    0.041
##     .Ineg_b6           0.365    0.061    5.939    0.000    0.365    0.035
##     .Ineg_b7           0.359    0.053    6.840    0.000    0.359    0.034
##     .Ineg_b8           0.422    0.058    7.311    0.000    0.422    0.040
##     .Ineg_b9           0.293    0.041    7.152    0.000    0.293    0.028
##     .Ineg_b10          0.477    0.066    7.175    0.000    0.477    0.045
##     .Ineg_b11          0.900    0.119    7.589    0.000    0.900    0.082
##     .Iaro_b1           0.294    0.043    6.909    0.000    0.294    0.023
##     .Iaro_b2           0.239    0.031    7.733    0.000    0.239    0.019
##     .Iaro_b3           0.273    0.050    5.511    0.000    0.273    0.022
##     .Iaro_b4           0.192    0.032    6.016    0.000    0.192    0.016
##     .Iaro_b5           0.241    0.038    6.361    0.000    0.241    0.019
##     .Iaro_b6           0.239    0.033    7.146    0.000    0.239    0.019
##     .Iaro_b7           0.280    0.056    4.955    0.000    0.280    0.022
##     .Iaro_b8           0.285    0.044    6.534    0.000    0.285    0.023
##     .Iaro_b9           0.300    0.050    6.018    0.000    0.300    0.024
##     .Iaro_b10          0.330    0.055    5.978    0.000    0.330    0.026
##     .Iaro_b11          0.544    0.077    7.058    0.000    0.544    0.043
##      RIpos            10.051    0.527   19.067    0.000    1.000    1.000
##      RIneg             9.433    0.453   20.820    0.000    1.000    1.000
##      RIaro            12.744    0.790   16.126    0.000    1.000    1.000
```

2.1 Three-Timepoint RI-CLPM

Model Fit
- CFI = 0.008, TLI = –0.19, RMSEA = 0.307, SRMR = 1.752 (poor overall fit)
- RIs nearly collinear (non–positive-definite latent covariances)

Trait Variance
- RIpos Var = 8.75, RIneg Var = 5.46, RIaro Var = 14.27 (all $p < .001$)

Within-Person Autoregression
- **Positive affect** ($a_1 = 0.359$, $p = .001$) and **negative affect** ($a_2 = 0.717$, $p < .001$) show significant carry-over

- **Arousal** (a_3 = –0.003, p = .974) no persistence

Cross-Lagged Effects
- **Negative → Positive** (b_1 = 0.661, $p < .001$)
- **Positive → Negative** (c_1 = 0.782, $p < .001$)
- **Arousal → Positive** (b_2 = –0.752, $p < .001$) and **Arousal → Negative** (c_2 = –1.079, $p < .001$) - **Valence → Arousal** non-significant

---

2.2 Block-Based RI-CLPM (11 Blocks)

Model Fit
- CFI = 0.722, TLI = 0.732, RMSEA = 0.144, SRMR = 7.95 (exploratory)

Within-Person Autoregression
- **Positive affect** mean-reversion (a_1 = –0.104, $p < .001$)
- **Negative affect** mean-reversion (a_2 = –0.112, $p < .001$)
- **Arousal** persistence (a_3 = 0.145, p = .001)

Cross-Lagged Effects
- **Negative → Positive** (b_1 = 0.239, $p < .001$)
- **Positive → Negative** (c_1 = 0.252, $p < .001$)
- **Arousal → Positive** (b_2 = –0.131, $p < .001$) and **Arousal → Negative** (c_2 = –0.099, p = .002) - **Positive → Arousal** (d_1 = –0.062, p = .017) and **Negative → Arousal** (d_2 = –0.132, $p < .001$)

2.3 Causal Implications

After removing trait variance and using strict lagged ordering, significant cross-lag paths represent **within-person causal dynamics**:

- A spike in negative affect leads to a subsequent rise in positive affect.
- A spike in positive affect leads to a subsequent rise in negative affect.
- Elevated arousal suppresses both positive and negative affect on the next occasion.

  Note: Poor overall fit means these patterns should be interpreted as preliminary insights, pending model refinement and robustness checks.