

RI-CLPM

Contents

1	Cross-lag paths (how one emotion affect another at the next time point) & Inertia	1
1.1	Difference in paths by sex	4
1.2	Difference in paths by ethnicity	9
1.3	Difference in paths by age	16
2	RI-CLPM (Random-Intercept)–Causality	17
2.1	Three-Timepoint RI-CLPM	29
2.2	Block-Based RI-CLPM (11 Blocks)	30
2.3	Causal Implications	30
3	trial.val -> inertia	30

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
```

```

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
- $\text{Ipos} \sim \text{Ineg_lag1}$ ($\beta = 0.166$, $p < .001$): negative emotion predicts positive emotion in the next moment, which might reflect emotional rebound
- $\text{Ineg} \sim \text{Ipos_lag1}$ ($\beta = 0.172$, $p < .001$): positive emotion enhances negative emotion in the next moment, which might reflect emotional mix or trial order effect
- $\text{Iaro} \sim \text{Ipos_lag1}$ ($\beta = -0.053$, $p < .001$): positive emotion decreases arousal at the later stage
- $\text{Iaro} \sim \text{Ineg_lag1}$ ($\beta = -0.078$, $p < .001$): negative emotion decreases arousal at the later stage
- $\text{Ipos} \sim \text{Iaro_lag1}$ and $\text{Ineg} \sim \text{Iaro_lag1}$ 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

```
# 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.
```

```
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
```

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

```
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 ($\beta = .43$, $p < .001$).
 - Both prior positive ($\beta = -.05$, $p = .031$) and negative emotion ($\beta = -.08$, $p < .001$) significantly reduced subsequent arousal
- Black/African American:
 - Strongest Ipos inertia ($\beta = .187$) among all groups ($p < .001$)
 - Arousal -> Positive emotion path is negative and significant ($\beta = -.085$, $p = .012$), suggesting arousal suppresses positivity here
- Latino/Hispanic:
 - Uniquely positive effect from prior arousal to later positive emotion ($\beta = .189$, $p < .001$).
 - Had the strongest Iaro inertia ($\beta = .483$, $p < .001$).
- White/Caucasian:
 - Negative cross-effects from both Ipos to Iaro ($\beta = -.104$, $p < .001$) and Ineg to Iaro ($\beta = -.119$, $p < .001$), 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 ($\beta = .21$, $p = .005$)
 - The only group where prior negative emotion significantly increased arousal ($\beta = .16$, $p = .037$)

1.3 Difference in paths by age

```
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_riclp3 <- '

# 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_riclp3 <- sem(
  model      = model_riclp3,
  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_riclp3, 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
```

```

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)
  )
})

```

```

}))

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

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

# 5) Output summary with standardized estimates and fit indices
summary(fit_blk_riclpn, 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
##      .Ipos_b2      0.000
##      .Ipos_b3      0.000
##      .Ipos_b4      0.000
##      .Ipos_b5      0.000
##      .Ipos_b6      0.000
##      .Ipos_b7      0.000
##      .Ipos_b8      0.000
##      .Ipos_b9      0.000
##      .Ipos_b10     0.000
##      .Ipos_b11     0.000
##      RIneg ~~
##      .Ineg_b1      0.000
##      .Ineg_b2      0.000
##      .Ineg_b3      0.000
##      .Ineg_b4      0.000
##      .Ineg_b5      0.000
##      .Ineg_b6      0.000
##      .Ineg_b7      0.000
##      .Ineg_b8      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.

3 trial.val -> inertia

Whether stimulus type affects the intensity of inertia?