

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	15
2	RI-CLPM (Random-Intercept)–Causality	16
2.1	Three-Timepoint RI-CLPM	29
2.2	Block-Based RI-CLPM (11 Blocks)	29
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

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_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_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_riclp <- paste(c(trait, ints, nocov, lags), collapse="\n")

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

# 5) Output summary with standardized estimates and fit indices
summary(fit_blk_riclp, 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** \rightarrow **Positive** ($b_1 = 0.661$, $p < .001$)
- **Positive** \rightarrow **Negative** ($c_1 = 0.782$, $p < .001$)
- **Arousal** \rightarrow **Positive** ($b_2 = -0.752$, $p < .001$) and **Arousal** \rightarrow **Negative** ($c_2 = -1.079$, $p < .001$) - **Valence** \rightarrow **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** \rightarrow **Positive** ($b_1 = 0.239$, $p < .001$)
- **Positive** \rightarrow **Negative** ($c_1 = 0.252$, $p < .001$)
- **Arousal** \rightarrow **Positive** ($b_2 = -0.131$, $p < .001$) and **Arousal** \rightarrow **Negative** ($c_2 = -0.099$, $p = .002$) - **Positive** \rightarrow **Arousal** ($d_1 = -0.062$, $p = .017$) and **Negative** \rightarrow **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?