**Supplemental Information**

**7.1. Correlations between key variables at baseline.**

All the key variables correlated significantly with each other at baseline. The lowest correlations were between pain grade and chronotype (*r* = .125), and the highest between insomnia symptoms and CEA pre-sleep behaviors (*r* = .532) and pain grade (*r* = .523). The delta-scores showed moderate correlations with the baseline-scores of the same measures (r = .553 to r = .459).

**7.2. Test of measurement invariance of the pain intensity measures.**

To explore whether the pain construct remained stable across time and if the deviation of the measures of abdominal pain intensity and headache intensity at timepoint 3 (for the last 2 months instead of for the last 6 months) had an effect on the measures, we tested each pain type for measurement invariance. To accomplish this, we first constructed latent variables of each pain type, where pain intensity, pain frequency and pain interference represented the manifest indicators for each pain type at each timepoint. These were subsequently incorporated into three longitudinal confirmatory factor analyses, and tested for configural invariance, metric/weak invariance and scalar/strong invariance. As can be seen in **Table S1** below, all pain types held for the assumption of strong measurement invariance, which indicates that the constructs remained stable across all timepoints and that the deviating time scaling at timepoint 3 did not have an impact on the constructs.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table S1**  Model fit statistics for the tests of invariance in the three longitudinal confirmatory factor analyses of musculoskeletal pain, headache and abdominal pain. | | | | | | | | |
| Model tested | ꭓ2 | | *Df* | *P* | RMSEA | RMSEA 90% CI | CFI | ΔCFI |
|  | | Model estimates | | | | | | |
| *Musculoskeletal pain* |  | |  |  |  |  |  |  |
| Null model | 17226.06 | | 66 | <.001 | --- | --- | --- | --- |
| Configural invariance | 162.99 | | 33 | <.001 | .038 | .032 - .044 | .992 | --- |
| Metric (weak) invariance | 169.20 | | 39 | <.001 | .035 | .030 - .040 | .992 | .000 |
| Scalar (strong) invariance | 216.53 | | 45 | <.001 | .037 | .032 - .042 | .990 | .002 |
| *Headache* |  | |  |  |  |  |  |  |
| Null model | 15734.21 | | 66 | <.001 | --- | --- | --- | --- |
| Configural invariance | 187.33 | | 33 | <.001 | .041 | .036 - .047 | .990 | --- |
| Metric (weak) invariance | 199.76 | | 39 | <.001 | .039 | .033 - .044 | .990 | .000 |
| Scalar (strong) invariance | 216.96 | | 45 | <.001 | .037 | .032 - .042 | .989 | .001 |
| *Abdominal pain* |  | |  |  |  |  |  |  |
| Null model | 14533.26 | | 66 | <.001 | --- | --- | --- | --- |
| Configural invariance | 205.66 | | 33 | <.001 | .044 | .038 - .049 | .988 | --- |
| Metric (weak) invariance | 231.28 | | 39 | <.001 | .042 | .037 - .048 | .987 | .001 |
| Scalar (strong) invariance | 246.81 | | 45 | <.001 | .040 | .036 - .045 | .986 | .001 |
| Note. Each longitudinal confirmatory factor analysis consisted of latent variables of pain that, in turn, were constructed from pain intensity, pain frequency and pain interference as manifest indicators. | | | | | | | | |

**7.4. On model fit indices and criteria.**

We considered the following two types of fit indices when assessing model fit: (1) An information criterion, which evaluates how well a model fits the data by taking into account model fit, model complexity and sample size. Lower values indicate a better fit. In the current study, we used the sample size – adjusted Bayesian Information Criteria (SS-ABIC) [2]. With a sample size as in the current study, model fit indices tend to increase ad finitum with increased number of classes, so we rather focused on the elbow curve; the point where the model fit indices improve less than before with increased classes, as an indication of the optimal class number [1]. (2) A likelihood ratio test, which compares the current number of classes (n) with n - 1 number of classes. A small *p* - value indicates that the current number of classes fits the data better than a model with one class less. In the current study, we used the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), which has been recommended as a robust test in previous literature [2]. In addition, we considered entropy, which is a standardized, averaged measure of how well individuals in the sample fits into their assigned class. Values range from 0 to 1, with 1 representing a perfect fit. Values of at least .40, .60 and .80 represent low, moderate and high class separation [32]. Entropy was not considered when determining the optimal number of classes, but indicated if the class-separation in the final model was sufficient [45]. We also opted for the model with the least restrictions on model parameters, since constraints on the model may bias results [55], while also encountering the least convergence problems, which may indicate that the model does not fit the data well [32]. Finally, we opted for the model with the least restrictions on model parameters, since constraints on the model may bias results [55], while also encountering the least convergence problems, which may indicate that the model does not fit the data well [32].

For incorporating the predictors into the GMM, we utilized the “Three-step approach”. Benefits of this approach is that the parameters of the mixture model are not influenced by the auxiliary predictor variable, while still accounting for uncertainty rate in class membership. It consists of three steps, as the name suggests: 1) estimating an unconditional GMM, 2) assigning individuals to latent classes while accounting for uncertainty of class membership, and 3) including predictors of the class-variable and within-class growth factors [45].

**7.5. Model building.**

First, linear growth curve models of insomnia symptoms and pain were constructed. They showed adequate fit to the data (*χ2*(22) = 289.44, *p* = .066, RMSEA = .066, CFI = .964) and significant variance in growth factors, which indicated unobserved heterogeneity in the growth curves that may be better explained via GMM. Adding quadratic growth factors was met with convergence issues, and there were not sufficient degrees of freedom to properly specify the quadratic model. Specifying latent basis growth curves improved model fit compared to the linear model (Δ *χ2*(4) = 17.59, *p* = .001, ΔRMSEA = .006, ΔCFI = .002). We therefore opted for basing the GMM on latent basis growth curves. Note that we also completed all analyses with linear growth curves, and they showed comparable results as with the latent basis growth curves.

Secondly, we explored the optimal class number in LCGA’s, and found the 4-class solution to be optimal. We then explored which level of GMM would fit the data best, via Wald χ2-tests. A model with class-invariant variances (GMM-CI) fitted the data significantly better than a zero-variance model (LCGA; Wald χ2(8) = 280.22, p < .001). When estimating a GMM with class-varying variances (GMM-CV), the intercept variances had to be constrained to be equal across classes, and the slope variances in the largest class had to be constrained to zero. Freeing the remaining three slope variances to be class-varying, compared to class-invariant, significantly improved the model (Wald χ2(13) = 28.01, *p* = .009). Note that this comparison did not take the plausibly negative effect of the zero-variance slope into account. Taken together, we opted for the more parsimonious GMM-CI as the best-fitting model, since it did not encounter convergence problems (which the GMM-CV did) and it yielded theoretically meaningful classes that facilitated interpretation. Third, we found that a four-class solution of a GMM with class-invariant variances fitted the data best, when comparing theoretical meaningfulness and model fit indices of 2 to 7 classes. **Table S2** below depicts specifics of the growth factors in the optimal 4-class class-invariant GMM.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table S2**. Class-specific growth parameters of the optimal 4-class unconditional multidimensional growth mixture model. | | | | | |
|  | Class 1  (n = 1893) | Class 2  (n = 134) | Class 3  (n = 383) | Class 4  (n = 345) |  |
| Insomnia intercept |  |  |  |  |  |
| Mean | 11.71 | 58.50 | 20.49 | 43.97 |  |
| (Variance) | (37.21ns) | (37.21ns) | (37.21ns) | (37.21ns) |  |
| Insomnia slope |  |  |  |  |  |
| Mean | 1.42 | 2.29ns | 11.50 | - 6.05 |  |
| (Variance) | (6.13ns) | (6.13ns) | (6.13ns) | (6.13ns) |  |
| Pain intercept |  |  |  |  |  |
| Mean | 15.81 | 44.64 | 22.88 | 36.40 |  |
| (Variance) | (195.71) | (195.71) | (195.71) | (195.71) |  |
| Pain slope |  |  |  |  |  |
| Mean | 0.96 | 2.00ns | 5.22 | - 1.37ns |  |
| (Variance) | (22.40ns) | (22.40ns) | (22.40ns) | (22.40ns) |  |
| Note. Unless otherwise stated, all estimated means and variances were significant at *p* < .001. NS = non-significant. | | | | | |

**7.6. Longitudinal descriptive data of the key variables.**

Longitudinal descriptive data of the key variables are depicted in **Table S3**. As can be seen, the values on the pain grades and insomnia symptoms increase in all classes except for in Class 4 (“Decreasing pain and insomnia”). This is to be expected, since both pain and insomnia increase across adolescence. Pre-sleep behaviors causing arousal increased across the four measurement occasions in the general sample, and the average chronotype shifted to be 19 minutes later from timepoint 1 to timepoint 4.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table S3**  Descriptive statistics for key variables at T1 to T4. | | | | |
|  |  | Timepoint | |  |
|  | 1 | 2 | 3 | 4 |
| Pain grade [0-100] |  |  |  |  |
| Class 1 | 15.96 | 16.20 | 17.23 | 18.92 |
| Class 2 | 45.32 | 45.47 | 49.33 | 45.73 |
| Class 3 | 23.24 | 28.01 | 33.83 | 36.18 |
| Class 4 | 36.57 | 34.12 | 33.80 | 33.19 |
| Insomnia symptoms [0-100] |  |  |  |  |
| Class 1 | 11.81 | 12.93 | 14.29 | 16.47 |
| Class 2 | 59.46 | 57.70 | 63.27 | 63.14 |
| Class 3 | 20.80 | 31.27 | 47.54 | 51.29 |
| Class 4 | 44.54 | 36.36 | 29.07 | 29.37 |
| Chronotype [hours:minutes] | 4:51 | 4:59 | 5:06 | 5:10 |
| CEA-PSB [0-30] | 8.14 | 8.95 | 9.75 | 10.19 |
| BA-PSB [0-15] | 8.11 | 9.06 | 10.00 | 10.54 |
| Note: All the means and standard deviations were estimated using full information maximum likelihood estimation (FIML). Pain grade and insomnia symptoms are presented in percentage of maximum score, the average score within each of the four classes. Regarding Chronotype, CEA pre-sleep behaviors and BA pre-sleep behaviors, the averages in the overall samples are presented.  CEA-PSB = Cognitive-emotional arousal-causing pre-sleep behaviors.  BA-PSB = Behavioral arousal-causing pre-sleep behaviors. | | | | |

**7.7. Multinomial regression analysis**

The tables below details the full multinomial regression analysis examining if chronotype and arousal-causing pre-sleep behaviors can predict class membership. **Table S4** has class 1 (low pain and insomnia) as reference class, and **Table S5** has class 2 (high pain and insomnia) as reference class.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table S4.** The influence of chronotype and arousal-causing pre-sleep behaviors on class membership, using multinominal logit regressions. Class 1 (low pain and insomnia) is the reference class. | | | |
|  | Class 1 versus Class 2 | Class 1 versus Class 3 | Class 1 versus Class 4 |
| Chronotype | **0.007\*** | **0.003\*** | **0.003\*** |
| CEA-PSB | **0.267\*** | **0.101\*** | **0.204\*** |
| BA-PSB | -0.011ns | 0.016ns | -0.012ns |
| Note. Unstandardized coefficients are shown. The predictors are measured at baseline (T1).  \**p*<.05*.*  *ns =* non-significant at *p* < .05 level.  CEA-PSB = Cognitive-emotional arousal-causing pre-sleep behaviors.  BA-PSB = Behavioral arousal-causing pre-sleep behaviors. | | | |

|  |  |  |  |
| --- | --- | --- | --- |
| **Table S5.** The influence of chronotype and arousal-causing pre-sleep behaviors on class membership, using multinominal logit regressions. Class 2 (high pain and insomnia) is the reference class. | | | |
|  | Class 2 versus Class 1 | Class 2 versus Class 3 | Class 2 versus Class 4 |
| Chronotype | **-0.007\*** | **-0.004\*** | **-0.004\*** |
| CEA-PSB | **-0.267\*** | **-0.167\*** | **-0.064\*** |
| BA-PSB | 0.011ns | 0.028ns | -0.001ns |
| Note. Unstandardized coefficients are shown. The predictors are measured at baseline (T1).  \**p*<.05*.*  *ns =* non-significant at *p* < .05 level.  CEA-PSB = Cognitive-emotional arousal-causing pre-sleep behaviors.  BA-PSB = Behavioral arousal-causing pre-sleep behaviors. | | | |

7.8. Mplus Syntax.

7.8.1. Multidimensional GMM

VARIABLE:

Names =

ID N4

gender age cult ses divorce stress dep anx ins dspd wspain1 wspain2

a\_ce b\_ce c\_ce d\_ce

a\_ba b\_ba c\_ba d\_ba

a\_sjl b\_sjl c\_sjl d\_sjl

a\_msf b\_msf c\_msf d\_msf

a\_ch b\_ch c\_ch d\_ch

sovtid wksov wesov

a\_pgmix b\_pgmix c\_pgmix d\_pgmix e\_pgmix

a\_intmix b\_intmix c\_intmix d\_intmix e\_intmix

a\_pgmax b\_pgmax c\_pgmax d\_pgmax e\_pgmax

a\_rint b\_rint c\_rint d\_rint e\_rint

a\_rfrq b\_rfrq c\_rfrq d\_rfrq e\_rfrq

a\_rinf b\_rinf c\_rinf d\_rinf e\_rinf

a\_hint b\_hint c\_hint d\_hint e\_hint

a\_hfrq b\_hfrq c\_hfrq d\_hfrq e\_hfrq

a\_hinf b\_hinf c\_hinf d\_hinf e\_hinf

a\_mint b\_mint c\_mint d\_mint e\_mint

a\_mfrq b\_mfrq c\_mfrq d\_mfrq e\_mfrq

a\_minf b\_minf c\_minf d\_minf e\_minf

a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7

b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7

c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7

d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7

e\_ps1 e\_ps2 e\_ps3 e\_ps4 e\_ps5 e\_ps6 e\_ps7;

Usevariables =

a\_cpg b\_cpg c\_cpg d\_cpg

a\_cisi b\_cisi c\_cisi d\_cisi;

Classes = c(4);

IDvariable = ID;

Missing =

gender age cult ses divorce stress dep anx ins dspd wspain1 wspain2

a\_ce b\_ce c\_ce d\_ce

a\_ba b\_ba c\_ba d\_ba

a\_pgmix b\_pgmix c\_pgmix d\_pgmix e\_pgmix

a\_intmix b\_intmix c\_intmix d\_intmix e\_intmix

a\_pgmax b\_pgmax c\_pgmax d\_pgmax e\_pgmax

a\_rint b\_rint c\_rint d\_rint e\_rint

a\_rfrq b\_rfrq c\_rfrq d\_rfrq e\_rfrq

a\_rinf b\_rinf c\_rinf d\_rinf e\_rinf

a\_hint b\_hint c\_hint d\_hint e\_hint

a\_hfrq b\_hfrq c\_hfrq d\_hfrq e\_hfrq

a\_hinf b\_hinf c\_hinf d\_hinf e\_hinf

a\_mint b\_mint c\_mint d\_mint e\_mint

a\_mfrq b\_mfrq c\_mfrq d\_mfrq e\_mfrq

a\_minf b\_minf c\_minf d\_minf e\_minf

a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7

b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7

c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7

d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7

e\_ps1 e\_ps2 e\_ps3 e\_ps4 e\_ps5 e\_ps6 e\_ps7 (-9)

a\_sjl b\_sjl c\_sjl d\_sjl

a\_msf b\_msf c\_msf d\_msf

a\_ch b\_ch c\_ch d\_ch

sovtid wksov wesov (-9.00);

savedata:

file='C:\....txt';

save=cprob;

missflag = -9;

DEFINE:

! T1 / Wave A

a\_isi = sum(a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7);

a\_cpg = (a\_pgmix/4)\*100;

a\_cisi =(a\_isi/28)\*100;

! T2 / Wave B

b\_isi = sum (b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7);

b\_cpg = (b\_pgmix/4)\*100;

b\_cisi = (b\_isi/28)\*100;

! T3 / Wave C

c\_isi = sum (c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7);

c\_cpg = (c\_pgmix/4)\*100;

c\_cisi = (c\_isi/28)\*100;

! T4 / Wave D

d\_isi = sum (d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7);

d\_cpg = (d\_pgmix/4)\*100;

d\_cisi = (d\_isi/28)\*100;

ANALYSIS:

type=mixture;

process=8;

starts=1000 50;

MODEL:

%overall%

i\_cpg s\_cpg | a\_cpg@0 b\_cpg@1 c\_cpg\* d\_cpg\*;

i\_cisi s\_cisi | a\_cisi@0 b\_cisi@1 c\_cisi\* d\_cisi\*;

a\_cisi with b\_cisi;

b\_cisi with c\_cisi;

c\_cisi with d\_cisi;

a\_cpg with b\_cpg;

b\_cpg with c\_cpg;

c\_cpg with d\_cpg;

a\_cpg with a\_cisi;

b\_cpg with b\_cisi;

c\_cpg with c\_cisi;

d\_cpg with d\_cisi;

i\_cpg (m1);

s\_cpg (m2);

i\_cisi (m3);

s\_cisi (m4);

i\_cpg with s\_cpg (c1);

i\_cisi with s\_cisi (c2);

i\_cpg with i\_cisi (c3);

s\_cpg with s\_cisi (c4);

7.8.1. Baseline comparisons.

Usevariables =

N2

!a\_msf a\_ce a\_ba

a\_cpg b\_cpg c\_cpg d\_cpg

a\_cisi b\_cisi c\_cisi d\_cisi;

!a\_isi;

!dlt\_msf dlt\_ce dlt\_ba;

Classes = c(4);

IDvariable = ID;

Nominal = N2;

Missing =

gender age cult ses divorce stress dep anx ins dspd wspain1 wspain2

a\_ce b\_ce c\_ce d\_ce

a\_ba b\_ba c\_ba d\_ba

a\_pgmix b\_pgmix c\_pgmix d\_pgmix e\_pgmix

a\_intmix b\_intmix c\_intmix d\_intmix e\_intmix

a\_pgmax b\_pgmax c\_pgmax d\_pgmax e\_pgmax

a\_rint b\_rint c\_rint d\_rint e\_rint

a\_rfrq b\_rfrq c\_rfrq d\_rfrq e\_rfrq

a\_rinf b\_rinf c\_rinf d\_rinf e\_rinf

a\_hint b\_hint c\_hint d\_hint e\_hint

a\_hfrq b\_hfrq c\_hfrq d\_hfrq e\_hfrq

a\_hinf b\_hinf c\_hinf d\_hinf e\_hinf

a\_mint b\_mint c\_mint d\_mint e\_mint

a\_mfrq b\_mfrq c\_mfrq d\_mfrq e\_mfrq

a\_minf b\_minf c\_minf d\_minf e\_minf

a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7

b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7

c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7

d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7

e\_ps1 e\_ps2 e\_ps3 e\_ps4 e\_ps5 e\_ps6 e\_ps7 (-9)

a\_sjl b\_sjl c\_sjl d\_sjl

a\_msf b\_msf c\_msf d\_msf

a\_ch b\_ch c\_ch d\_ch

sovtid wksov wesov (-9.00);

Auxiliary = gender (dcat) dep (dcat) anx (dcat) ins (dcat) wspain2 (dcat) cult (dcat) ses (dcat);

Auxiliary = ses (du3step) stress (du3step) a\_isi (du3step) a\_msf (du3step) a\_ce (du3step) a\_ba (du3step) a\_pgmix (du3step) a\_sjl (du3step) sovtid (du3step) wksov (du3step) wesov (du3step) a\_rint (du3step) a\_hint (du3step) a\_mint (du3step) a\_rfrq (du3step) a\_hfrq (du3step) a\_mfrq (du3step) a\_rinf (du3step) a\_hinf (du3step) a\_minf (du3step) a\_msf (du3step) age (du3step) wksov (du3step) wesov (du3step);

Auxiliary = dlt\_msf (du3step) dlt\_ce (du3step) dlt\_ba (du3step);

DEFINE:

! T1 / Wave A

a\_isi = sum (a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7);

a\_cpg = (a\_pgmix/4)\*100;

a\_cisi = (a\_isi/28)\*100;

! T2 / Wave B

b\_isi = sum (b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7);

b\_cpg = (b\_pgmix/4)\*100;

b\_cisi = (b\_isi/28)\*100;

! T3 / Wave C

c\_isi = sum (c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7);

c\_cpg = (c\_pgmix/4)\*100;

c\_cisi = (c\_isi/28)\*100;

! T4 / Wave D

d\_isi = sum (d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7);

d\_cpg = (d\_pgmix/4)\*100;

d\_cisi = (d\_isi/28)\*100;

ANALYSIS:

type = mixture;

process = 8;

starts = 1000 50;

optseed =

!21132;

!843555;

!432148;

MODEL:

%overall%

i\_cpg s\_cpg | a\_cpg@0 b\_cpg@1 c\_cpg\* d\_cpg\*;

i\_cisi s\_cisi | a\_cisi@0 b\_cisi@1 c\_cisi\* d\_cisi\*;

a\_cisi with b\_cisi;

b\_cisi with c\_cisi;

c\_cisi with d\_cisi;

a\_cpg with b\_cpg;

b\_cpg with c\_cpg;

c\_cpg with d\_cpg;

a\_cpg with a\_cisi;

b\_cpg with b\_cisi;

c\_cpg with c\_cisi;

d\_cpg with d\_cisi;

i\_cpg;

s\_cpg;

i\_cisi;

s\_cisi;

i\_cpg with s\_cpg;

i\_cisi with s\_cisi;

i\_cpg with i\_cisi;

s\_cpg with s\_cisi;

%C#1%

[N2#1@11.297];[N2#2@7.306];[N2#3@7.711];

%C#2%

[N2#1@1.145];[N2#2@2.903];[N2#3@0.254];

%C#3%

[N2#1@3.219];[N2#2@1.671];[N2#3@4.289];

%C#4%

[N2#1@-4.727];[N2#2@-1.542];[N2#3@-2.729];

7.8.2. Multinomial analysis.

Usevariables =

N2

a\_msf a\_ba a\_ce

a\_cpg b\_cpg c\_cpg d\_cpg

a\_cisi b\_cisi c\_cisi d\_cisi;

Classes = c(4);

IDvariable = ID;

Nominal = N2;

Missing =

gender age cult ses divorce dep anx stress ins dspd wspain1 wspain2

a\_ce b\_ce c\_ce d\_ce

a\_ba b\_ba c\_ba d\_ba

a\_pgmix b\_pgmix c\_pgmix d\_pgmix

a\_intmix b\_intmix c\_intmix d\_intmix

a\_pgmax b\_pgmax c\_pgmax d\_pgmax

a\_rint b\_rint c\_rint d\_rint

a\_rfrq b\_rfrq c\_rfrq d\_rfrq

a\_rinf b\_rinf c\_rinf d\_rinf

a\_hint b\_hint c\_hint d\_hint

a\_hfrq b\_hfrq c\_hfrq d\_hfrq

a\_hinf b\_hinf c\_hinf d\_hinf

a\_mint b\_mint c\_mint d\_mint

a\_mfrq b\_mfrq c\_mfrq d\_mfrq

a\_minf b\_minf c\_minf d\_minf

a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7

b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7

c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7

d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7 (-9)

a\_sjl b\_sjl c\_sjl d\_sjl

a\_msf b\_msf c\_msf d\_msf

a\_ch b\_ch c\_ch d\_ch

sovtid wksov wesov (-9.00);

Auxiliary = (r3step) a\_ba a\_ce a\_msf ;

DEFINE:

! T1 / Wave A

a\_isi = sum (a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7);

a\_cpg = (a\_pgmix/4)\*100;

a\_cisi = (a\_isi/28)\*100;

! T2 / Wave B

b\_isi = sum (b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7);

b\_cpg = (b\_pgmix/4)\*100;

b\_cisi = (b\_isi/28)\*100;

! T3 / Wave C

c\_isi = sum (c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7);

c\_cpg = (c\_pgmix/4)\*100;

c\_cisi = (c\_isi/28)\*100;

! T4 / Wave D

d\_isi = sum (d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7);

d\_cpg = (d\_pgmix/4)\*100;

d\_cisi = (d\_isi/28)\*100;

ANALYSIS:

type = mixture;

process = 8;

starts = 300 30;

!optseed =

!21132;

MODEL:

%overall%

%C#1%

[N2#1@11.297];[N2#2@7.306];[N2#3@7.711];

%C#2%

[N2#1@1.145];[N2#2@2.903];[N2#3@0.254];

%C#3%

[N2#1@3.219];[N2#2@1.671];[N2#3@4.289];

%C#4%

[N2#1@-4.727];[N2#2@-1.542];[N2#3@-2.729];

7.8.3. Within-class analysis.

Usevariables =

N2

a\_msf a\_ce a\_ba

a\_cpg b\_cpg c\_cpg d\_cpg

a\_cisi b\_cisi c\_cisi d\_cisi

dlt\_msf dlt\_ce dlt\_ba;

Classes = c(4);

IDvariable = ID;

Nominal = N2;

Missing =

gender age cult ses divorce stress dep anx ins dspd wspain1 wspain2

a\_ce b\_ce c\_ce d\_ce

a\_ba b\_ba c\_ba d\_ba

a\_pgmix b\_pgmix c\_pgmix d\_pgmix e\_pgmix

a\_intmix b\_intmix c\_intmix d\_intmix e\_intmix

a\_pgmax b\_pgmax c\_pgmax d\_pgmax e\_pgmax

a\_rint b\_rint c\_rint d\_rint e\_rint

a\_rfrq b\_rfrq c\_rfrq d\_rfrq e\_rfrq

a\_rinf b\_rinf c\_rinf d\_rinf e\_rinf

a\_hint b\_hint c\_hint d\_hint e\_hint

a\_hfrq b\_hfrq c\_hfrq d\_hfrq e\_hfrq

a\_hinf b\_hinf c\_hinf d\_hinf e\_hinf

a\_mint b\_mint c\_mint d\_mint e\_mint

a\_mfrq b\_mfrq c\_mfrq d\_mfrq e\_mfrq

a\_minf b\_minf c\_minf d\_minf e\_minf

a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7

b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7

c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7

d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7

e\_ps1 e\_ps2 e\_ps3 e\_ps4 e\_ps5 e\_ps6 e\_ps7 (-9)

a\_sjl b\_sjl c\_sjl d\_sjl

a\_msf b\_msf c\_msf d\_msf

a\_ch b\_ch c\_ch d\_ch

sovtid wksov wesov (-9.00);

DEFINE:

! T1 / Wave A

a\_isi = sum (a\_ps1 a\_ps2 a\_ps3 a\_ps4 a\_ps5 a\_ps6 a\_ps7);

a\_cpg = (a\_pgmix/4)\*100;

a\_cisi = (a\_isi/28)\*100;

! T2 / Wave B

b\_isi = sum (b\_ps1 b\_ps2 b\_ps3 b\_ps4 b\_ps5 b\_ps6 b\_ps7);

b\_cpg = (b\_pgmix/4)\*100;

b\_cisi = (b\_isi/28)\*100;

! T3 / Wave C

c\_isi = sum (c\_ps1 c\_ps2 c\_ps3 c\_ps4 c\_ps5 c\_ps6 c\_ps7);

c\_cpg = (c\_pgmix/4)\*100;

c\_cisi = (c\_isi/28)\*100;

! T4 / Wave D

d\_isi = sum (d\_ps1 d\_ps2 d\_ps3 d\_ps4 d\_ps5 d\_ps6 d\_ps7);

d\_cpg = (d\_pgmix/4)\*100;

d\_cisi = (d\_isi/28)\*100;

ANALYSIS:

type = mixture;

process = 8;

!lrtstarts = 0 0 40 8;

starts = 200 20;

!stiterations = 10;

!lrtbootstrap = 50;

optseed =

21132;

!843555;

!432148;

MODEL:

%overall%

i\_cpg s\_cpg | a\_cpg@0 b\_cpg@1 c\_cpg\* d\_cpg\*;

i\_cisi s\_cisi | a\_cisi@0 b\_cisi@1 c\_cisi\* d\_cisi\*;

a\_cisi with b\_cisi;

b\_cisi with c\_cisi;

c\_cisi with d\_cisi;

a\_cpg with b\_cpg;

b\_cpg with c\_cpg;

c\_cpg with d\_cpg;

a\_cpg with a\_cisi;

b\_cpg with b\_cisi;

c\_cpg with c\_cisi;

d\_cpg with d\_cisi;

i\_cpg;

s\_cpg;

i\_cisi;

s\_cisi;

i\_cpg with s\_cpg;

i\_cisi with s\_cisi;

i\_cpg with i\_cisi;

s\_cpg with s\_cisi;

a\_msf;

a\_ce;

a\_ba;

dlt\_msf;

dlt\_ce;

dlt\_ba;

s\_cpg on a\_msf a\_ce a\_ba;

s\_cisi on a\_msf a\_ce a\_ba;

i\_cpg on a\_msf a\_ce a\_ba;

i\_cisi on a\_msf a\_ce a\_ba;

s\_cpg on dlt\_msf dlt\_ce dlt\_ba;

s\_cisi on dlt\_msf dlt\_ce dlt\_ba;

a\_msf with a\_ce@0;

a\_msf with a\_ba@0;

a\_ba with a\_ce@0;

dlt\_msf with a\_msf@0;

dlt\_msf with a\_ce@0;

dlt\_msf with a\_ba@0;

dlt\_ce with a\_ce@0;

dlt\_ce with a\_ba@0;

dlt\_ce with a\_msf@0;

dlt\_ba with a\_ba@0;

dlt\_ba with a\_ce@0;

dlt\_ba with a\_msf@0;

dlt\_msf with dlt\_ba@0;

dlt\_msf with dlt\_ce@0;

dlt\_ba with dlt\_ce@0;

%C#1%

[N2#1@11.297];[N2#2@7.306];[N2#3@7.711];

%C#2%

[N2#1@1.145];[N2#2@2.903];[N2#3@0.254];

%C#3%

[N2#1@3.219];[N2#2@1.671];[N2#3@4.289];

%C#4%

[N2#1@-4.727];[N2#2@-1.542];[N2#3@-2.729];

7.9. Variance-covariance matrix.

Covariances

A\_MSF A\_CE A\_BA A\_CPG B\_CPG

\_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_

A\_MSF 7032.670

A\_CE 78.707 38.055

A\_BA 73.021 10.084 14.422

A\_CPG 209.423 57.932 16.297 468.923

B\_CPG 172.443 48.537 13.186 260.755 509.205

C\_CPG 178.290 51.577 12.227 274.046 338.663

D\_CPG 200.921 45.700 10.275 257.159 336.901

A\_CISI 326.151 57.786 17.216 198.455 157.874

B\_CISI 203.048 47.705 13.191 159.934 222.719

C\_CISI 282.030 45.060 12.787 152.153 192.353

D\_CISI 314.763 49.872 13.296 145.101 188.449

DLT\_MSF -3983.841 -44.183 -33.283 -128.441 -113.930

DLT\_CE -29.609 -17.997 -4.090 -14.324 2.527

DLT\_BA -51.042 -6.175 -9.082 -7.288 -4.702

Covariances

C\_CPG D\_CPG A\_CISI B\_CISI C\_CISI

\_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_

C\_CPG 574.235

D\_CPG 401.351 591.845

A\_CISI 164.123 141.512 310.932

B\_CISI 202.568 187.688 194.174 338.973

C\_CISI 266.789 228.827 190.598 239.031 406.940

D\_CISI 236.535 280.140 180.850 229.167 290.335

DLT\_MSF -65.150 -120.506 -145.750 -24.746 -76.417

DLT\_CE 19.934 31.945 -18.412 2.863 13.334

DLT\_BA 0.463 3.969 -10.393 -3.565 -5.855

Covariances

D\_CISI DLT\_MSF DLT\_CE DLT\_BA

\_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_

D\_CISI 456.276

DLT\_MSF 1.695 7500.544

DLT\_CE 29.741 56.421 40.858

DLT\_BA 0.765 52.193 8.758 17.035