

Illustrative Example

For the manuscript “Classification Accuracy of Multidimensional Tests: Quantifying the Impact of Noninvariance”

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```
library(lavaan)
library(tidyverse)
library(knitr)
library(kableExtra)
library(broom)
```

```
# Load the provided code `PartInv_multi.R`
source(here::here("PartInv_multi.R"))
```

Import data

The data are part of the supplemental materials by Oct et al. (2020),¹ and can be obtained at <https://journals.sagepub.com/doi/suppl/10.1177/1073191119885018>

```
data <- read.table(here::here("IPIPFFM.dat"),
  header = TRUE)
```

Specify the model

Preliminary analysis showed eight pairs of unique factor covariances need to be freed: A2 and A5, E4 and E7, I2 and I10, I8 and I9, A9 and I9, C3 and E6, A2 and E7, E7 and N2.

¹Ock, J., McAbee, S. T., Mulfinger, E., & Oswald, F. L. (2020). The practical effects of measurement invariance: Gender invariance in two Big Five personality measures. *Assessment*, 27(4), 657-674. <https://doi.org/10.1177/1073191119885018>

```

model <- 'A =~ a2 + a5 + a7 + a9
          C =~ c3 + c4 + c8 + c9
          E =~ e1 + e4 + e6 + e7
          N =~ n1 + n2 + n6 + n8
          O =~ i2 + i8 + i9 + i10
          a2 ~~ a5
          e4 ~~ e7
          i2 ~~ i10
          i8 ~~ i9
          a9 ~~ i9
          c3 ~~ e6
          a2 ~~ e7
          e7 ~~ n2'

```

Conventional measurement invariance testing suggested the mini-IPIP scale support partial strict invariance across gender. Specifically, four items showed noninvariant intercepts across groups and three items showed noninvariant unique factor variance across groups. The results did not provide information on how these noninvariances may impact personnel selection using the mini-IPIP, so we demonstrated the MCAA framework in this example.

```

fit_strict <- cfa(model, data = data, group = "sex",
                  group.equal = c("loadings", "Intercepts", "residuals"),
                  group.partial = c("e6 ~ 1", "n1 ~ 1", "n2 ~ 1", "a2 ~ 1",
                                     "n2 ~~ n2", "n1 ~~ n1", "c8 ~~ c8"),
                  estimator = "MLR", std.lv = TRUE)

```

```

# Fit indices
knitr::kable(
  broom::glance(fit_strict) %>%
    select(AIC, BIC, cfi, chisq, npar, rmsea, srmr, tli, nobs),
  format = "markdown",
  digits = 3
)

```

AIC	BIC	cfi	chisq	npars	rmsea	srmr	tli	nobs
31033.99	31523.85	0.949	464.056	113	0.035	0.057	0.945	564

```

# extract parameter estimates
result <- lavInspect(fit_strict, what = "est")

```

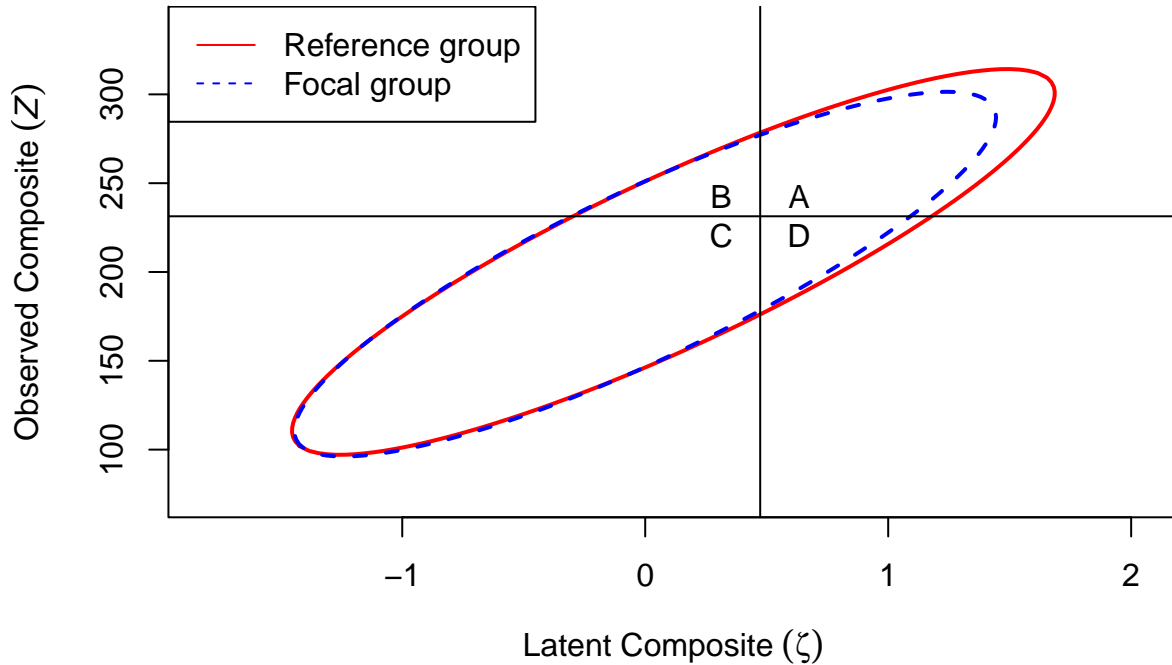
Step 1: Selection Parameters

Because the population sizes for females and for males are roughly equal, we used a mixing proportion(π_g) of 0.5. The weights for latent factors and items were calculated based on the predictive validities reported by previous study (Drasgow et al., 2012). The codes for obtaining the weights can be found in the supplementary materials. For the selection cutoff, we assume that the mini-IPIP is used to select the top 25% of the candidates.

Step 2: Selection Accuracy Under Strict Invariance

To establish the baseline information of using the mini-IPIP for selecting males and females, we first obtained the parameter estimates under full strict invariance. The codes for extracting parameter estimates from *lavaan* model object are provided in the supplementary materials. Our function enables researchers to visualize and quantify the impact of item bias on selection accuracy indices. From the table, we can conclude female candidates would be selected in a slightly higher proportion compared to male candidates if strict invariance holds.

```
strict <- PartInvMulti_we(propsel = .25,  
  weights_item = c(3.1385, 3.1385, 3.1385, 3.1385,  
    8.3203, 8.3203, 8.3203, 8.3203,  
    5.1586, 5.1586, 5.1586, 5.1586,  
    -6.5870, -6.5870, -6.5870, -6.5870,  
    1.7957, 1.7957, 1.7957, 1.7957),  
  # Agreeableness Conscientiousness Extraversion Neuroticism Openness  
  weights_latent = c(0.1256, 0.3328, 0.2063, -0.2635, 0.0718),  
  alpha_r = result[[2]]$alpha,  
  alpha_f = result[[1]]$alpha,  
  psi_r = result[[2]]$psi,  
  psi_f = result[[1]]$psi,  
  lambda_r = (result[[2]]$lambda + result[[1]]$lambda) / 2,  
  nu_r = (result[[2]]$nu + result[[1]]$nu) / 2,  
  Theta_r = (result[[2]]$theta + result[[1]]$theta) / 2)
```



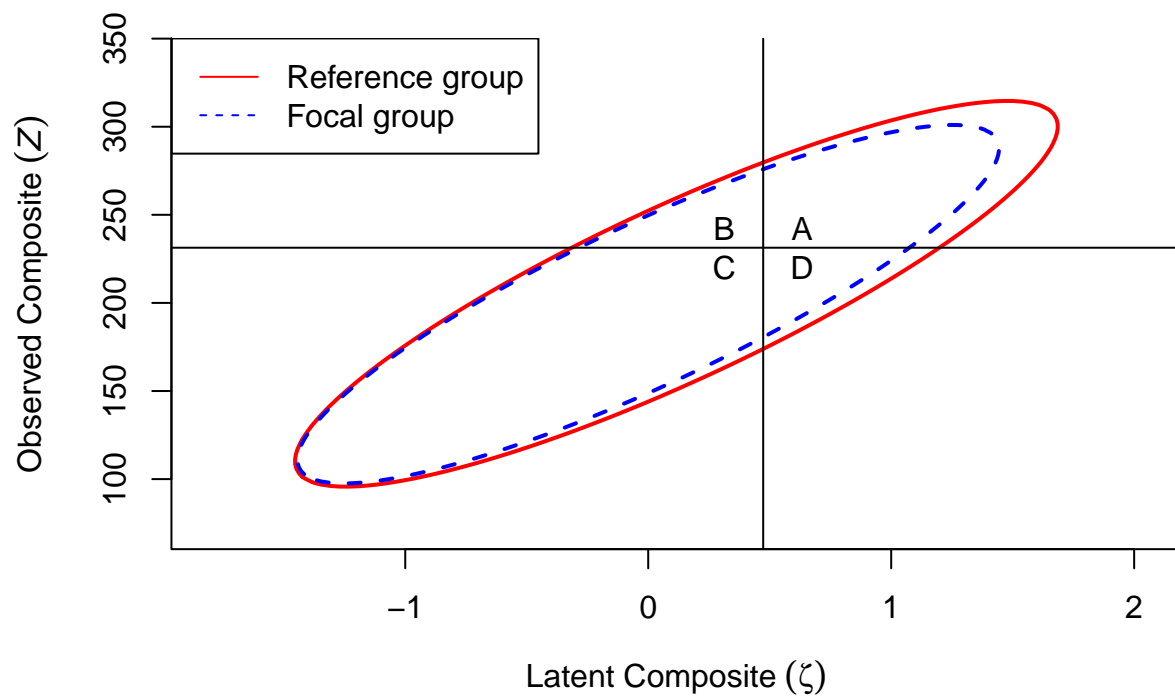
```
strict[1:5]
```

```
## $proposel
## [1] 0.25
##
## $cutpt_xi
## [1] 0.4732752
##
## $cutpt_z
## [1] 231.3604
##
## $summary
##
##           Reference Focal E_R.Focal.
## A (true positive)      0.217 0.153      0.217
## B (false positive)     0.064 0.066      0.064
## C (true negative)      0.647 0.723      0.647
## D (false negative)     0.072 0.058      0.072
## Proportion selected    0.281 0.219      0.281
## Success ratio          0.771 0.700      0.771
## Sensitivity             0.751 0.725      0.751
## Specificity            0.909 0.917      0.909
##
## $ai_ratio
## [1] 1
```

Step 3: Selection Accuracy Under Partial Strict Invariance

The selection accuracy of mini-IPIP under partial strict invariance can be obtained in the same way as in Step 2, except that `nu_r` and `nu_f` were different for males and for females, as well as `Theta_r` and `Theta_f`. The column $E_F(\text{Male})$ represents the expected proportion selected for male candidates based on the latent score distributions of the female candidates. The AI ratio for male candidates is estimated to be 0.935, indicating a slight disadvantage for male candidates when doing selection using the mini-IPIP.

```
par_strict <- PartInvMulti_we(proposel = .25,
  weights_item = c(3.1385, 3.1385, 3.1385, 3.1385,
    8.3203, 8.3203, 8.3203, 8.3203,
    5.1586, 5.1586, 5.1586, 5.1586,
    -6.5870, -6.5870, -6.5870, -6.5870,
    1.7957, 1.7957, 1.7957, 1.7957),
  # Agreeableness Conscientiousness Extraversion Neuroticism Openness
  weights_latent = c(0.1256, 0.3328, 0.2063, -0.2635, 0.0718),
  alpha_r = result[[2]]$alpha,
  alpha_f = result[[1]]$alpha,
  psi_r = result[[2]]$psi,
  psi_f = result[[1]]$psi,
  lambda_r = result[[2]]$lambda,
  nu_r = result[[2]]$nu,
  nu_f = result[[1]]$nu,
  Theta_r = result[[2]]$theta,
  Theta_f = result[[1]]$theta)
```



```
par_strict[1:5]
```

```
## $proptel
## [1] 0.25
##
## $cutpt_xi
## [1] 0.4732752
##
## $cutpt_z
## [1] 231.3297
##
## $summary
##               Reference Focal E_R.Focal.
## A (true positive)      0.214 0.155      0.220
## B (false positive)     0.065 0.065      0.064
## C (true negative)      0.646 0.724      0.648
## D (false negative)     0.075 0.056      0.069
## Proportion selected    0.279 0.220      0.284
## Success ratio          0.766 0.706      0.775
## Sensitivity             0.741 0.736      0.761
## Specificity             0.908 0.918      0.910
##
## $ai_ratio
## [1] 1.015058
```

Step 4: Compare the Change in Selection Accuracy indices

Comparing the results in Steps 2 and 3, researchers can quantify the impact of item bias on selection accuracy indices. In this example, we see in the presence of item bias, male candidates are selected in a lower proportion compared to when strict invariance holds (24.0% as opposed to 24.8%), whereas female candidates are selected in a higher proportion compared to when strict invariance holds (26.0% as opposed to 25.2%).

Table 2: Impact of Item Bias on Selection Accuracy Indices

	Female	Male	$E_F(\text{Male})$	Female	Male	$E_F(\text{Male})$
Proportion selected	0.281	0.219	0.281	0.279	0.220	0.284
Success ratio	0.771	0.700	0.771	0.766	0.706	0.775
Sensitivity	0.751	0.725	0.751	0.741	0.736	0.761
Specificity	0.909	0.917	0.909	0.908	0.918	0.910

Note: The column $E_F(\text{Male})$ shows the expected proportion for male candidates if the latent distributions are the same for both genders.

Compare MCAA With Separate Unidimensional Analyses

Compare Partial Invariance With Dropping Noninvariant items

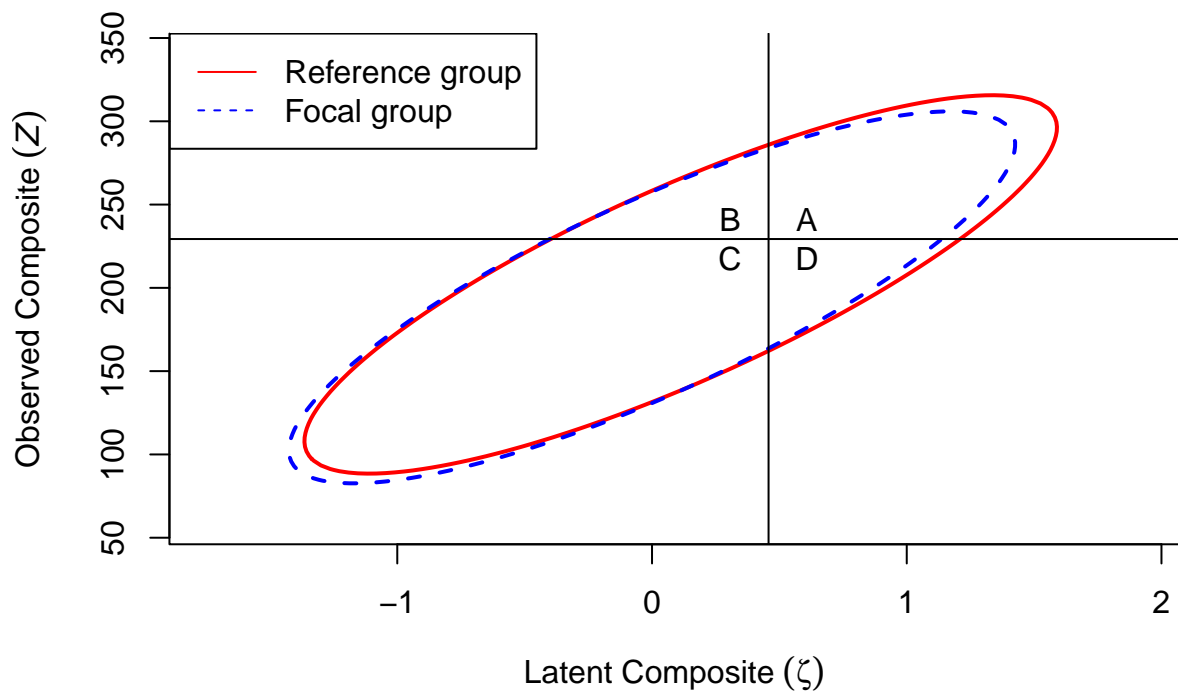
Sometimes researchers may want to remove the noninvariant items in the selection criteria. While this removes item biases, it may result in less effective classification due to reduced test length and thus decreased reliability. To illustrate this, we rerun MCAA without the items that showed noninvariance across genders (i.e., A2, C8, E6, N1, and N2). The table below shows

```
# Try removing noninvariant items (A2, )
model_reduced <- "A =~ a5 + a7 + a9
                  C =~ c3 + c4 + c9
                  E =~ e1 + e4 + e7
                  N =~ ln * n6 + ln * n8
                  O =~ i2 + i8 + i9 + i10
                  e4 ~~ e7
                  i2 ~~ i10
                  i8 ~~ i9
                  a9 ~~ i9"
fit_reduced <- cfa(model_reduced,
  data = data, group = "sex",
  group.equal = c("loadings", "Intercepts", "residuals"),
  estimator = "MLR", std.lv = TRUE
)
pars_reduced <- lavInspect(fit_reduced, what = "est")
reduced <- PartInvMulti_we(
  propsel = .25,
  weights_item = c(c(3.1385, 3.1385, 3.1385) * 4 / 3,
    c(8.3203, 8.3203, 8.3203) * 4 / 3,
    c(5.1586, 5.1586, 5.1586) * 4 / 3,
    c(-6.5870, -6.5870) * 4 / 2,
    1.7957, 1.7957, 1.7957, 1.7957),
```

```

weights_latent = c(0.1256, 0.3328, 0.2063, -0.2635, 0.0718),
alpha_r = pars_reduced[[2]]$alpha,
alpha_f = pars_reduced[[1]]$alpha,
psi_r = pars_reduced[[2]]$psi,
psi_f = pars_reduced[[1]]$psi,
lambda_r = pars_reduced[[1]]$lambda,
nu_r = pars_reduced[[1]]$nu,
Theta_r = pars_reduced[[1]]$theta
)

```



The table below shows lower selection accuracy with 15 invariant items for both groups, compared to 20 items with the five biased items.

Table 3: Impact of Item Bias on Selection Accuracy Indices

	Female	Male	$E_F(\text{Male})$
Proportion selected	0.279	0.221	0.279
Success ratio	0.724	0.669	0.724
Sensitivity	0.710	0.686	0.710
Specificity	0.892	0.907	0.892

Appendix: Parameter estimates for the partial strict invariance model

```
# Show parameter estimates
parameterEstimates(fit_strict)
```

##	lhs	op	rhs	block	group	label	est	se	z	pvalue	ci.lower	ci.upper
## 1	A	=~	a2	1	1	.p1.	0.322	0.055	5.878	0.000	0.215	0.429
## 2	A	=~	a5	1	1	.p2.	0.655	0.060	10.841	0.000	0.537	0.773
## 3	A	=~	a7	1	1	.p3.	0.645	0.054	11.912	0.000	0.539	0.751
## 4	A	=~	a9	1	1	.p4.	0.745	0.056	13.284	0.000	0.636	0.855
## 5	C	=~	c3	1	1	.p5.	0.570	0.052	10.947	0.000	0.468	0.672
## 6	C	=~	c4	1	1	.p6.	0.341	0.049	7.037	0.000	0.246	0.436
## 7	C	=~	c8	1	1	.p7.	0.398	0.049	8.100	0.000	0.301	0.494
## 8	C	=~	c9	1	1	.p8.	0.745	0.081	9.170	0.000	0.586	0.905
## 9	E	=~	e1	1	1	.p9.	0.657	0.050	13.147	0.000	0.559	0.755
## 10	E	=~	e4	1	1	.p10.	0.803	0.069	11.594	0.000	0.667	0.939
## 11	E	=~	e6	1	1	.p11.	0.799	0.062	12.841	0.000	0.677	0.920
## 12	E	=~	e7	1	1	.p12.	0.686	0.062	10.993	0.000	0.564	0.808
## 13	N	=~	n1	1	1	.p13.	0.507	0.057	8.964	0.000	0.396	0.618
## 14	N	=~	n2	1	1	.p14.	0.824	0.063	13.080	0.000	0.701	0.948
## 15	N	=~	n6	1	1	.p15.	0.600	0.053	11.245	0.000	0.495	0.704
## 16	N	=~	n8	1	1	.p16.	0.825	0.064	12.803	0.000	0.699	0.952
## 17	O	=~	i2	1	1	.p17.	0.512	0.081	6.356	0.000	0.354	0.670
## 18	O	=~	i8	1	1	.p18.	0.425	0.080	5.344	0.000	0.269	0.581
## 19	O	=~	i9	1	1	.p19.	0.485	0.075	6.457	0.000	0.338	0.632
## 20	O	=~	i10	1	1	.p20.	0.570	0.091	6.273	0.000	0.392	0.748
## 21	a2	~~	a5	1	1		0.172	0.041	4.221	0.000	0.092	0.252
## 22	e4	~~	e7	1	1		-0.107	0.078	-1.379	0.168	-0.259	0.045
## 23	i2	~~	i10	1	1		0.312	0.089	3.521	0.000	0.138	0.486
## 24	i8	~~	i9	1	1		0.457	0.098	4.653	0.000	0.265	0.650
## 25	a9	~~	i9	1	1		0.149	0.047	3.145	0.002	0.056	0.242
## 26	c3	~~	e6	1	1		-0.232	0.074	-3.136	0.002	-0.377	-0.087
## 27	a2	~~	e7	1	1		0.012	0.045	0.269	0.788	-0.076	0.100
## 28	e7	~~	n2	1	1		-0.023	0.050	-0.451	0.652	-0.121	0.076
## 29	a2	~~	a2	1	1	.p29.	0.544	0.050	10.946	0.000	0.447	0.641
## 30	a5	~~	a5	1	1	.p30.	0.536	0.055	9.759	0.000	0.429	0.644
## 31	a7	~~	a7	1	1	.p31.	0.410	0.053	7.704	0.000	0.306	0.515
## 32	a9	~~	a9	1	1	.p32.	0.356	0.054	6.611	0.000	0.251	0.462
## 33	c3	~~	c3	1	1	.p33.	0.935	0.074	12.559	0.000	0.789	1.081
## 34	c4	~~	c4	1	1	.p34.	0.410	0.039	10.578	0.000	0.334	0.486
## 35	c8	~~	c8	1	1		0.495	0.064	7.756	0.000	0.370	0.620
## 36	c9	~~	c9	1	1	.p36.	0.925	0.115	8.019	0.000	0.699	1.151
## 37	e1	~~	e1	1	1	.p37.	0.784	0.058	13.555	0.000	0.671	0.898
## 38	e4	~~	e4	1	1	.p38.	0.991	0.090	11.035	0.000	0.815	1.168
## 39	e6	~~	e6	1	1	.p39.	0.881	0.073	12.136	0.000	0.739	1.023
## 40	e7	~~	e7	1	1	.p40.	0.612	0.069	8.919	0.000	0.477	0.746
## 41	n1	~~	n1	1	1		0.663	0.083	7.966	0.000	0.500	0.826
## 42	n2	~~	n2	1	1		0.570	0.092	6.221	0.000	0.390	0.749
## 43	n6	~~	n6	1	1	.p43.	0.748	0.059	12.641	0.000	0.632	0.864
## 44	n8	~~	n8	1	1	.p44.	0.652	0.075	8.691	0.000	0.505	0.799
## 45	i2	~~	i2	1	1	.p45.	0.735	0.090	8.123	0.000	0.558	0.912
## 46	i8	~~	i8	1	1	.p46.	1.182	0.094	12.529	0.000	0.997	1.367
## 47	i9	~~	i9	1	1	.p47.	1.015	0.090	11.268	0.000	0.839	1.192

## 48	i10	~~	i10	1	1	.p48.	0.786	0.122	6.449	0.000	0.547	1.024
## 49	A	~~	A	1	1		1.000	0.000	NA	NA	1.000	1.000
## 50	C	~~	C	1	1		1.000	0.000	NA	NA	1.000	1.000
## 51	E	~~	E	1	1		1.000	0.000	NA	NA	1.000	1.000
## 52	N	~~	N	1	1		1.000	0.000	NA	NA	1.000	1.000
## 53	O	~~	O	1	1		1.000	0.000	NA	NA	1.000	1.000
## 54	A	~~	C	1	1		0.031	0.098	0.313	0.754	-0.162	0.223
## 55	A	~~	E	1	1		0.398	0.091	4.383	0.000	0.220	0.576
## 56	A	~~	N	1	1		-0.191	0.097	-1.960	0.050	-0.381	0.000
## 57	A	~~	O	1	1		0.416	0.113	3.676	0.000	0.194	0.638
## 58	C	~~	E	1	1		0.052	0.106	0.485	0.627	-0.157	0.260
## 59	C	~~	N	1	1		-0.159	0.104	-1.523	0.128	-0.364	0.046
## 60	C	~~	O	1	1		-0.009	0.134	-0.070	0.944	-0.272	0.253
## 61	E	~~	N	1	1		-0.041	0.101	-0.405	0.685	-0.239	0.157
## 62	E	~~	O	1	1		0.672	0.103	6.503	0.000	0.470	0.875
## 63	N	~~	O	1	1		-0.059	0.129	-0.458	0.647	-0.311	0.194
## 64	a2	~1		1	1		3.944	0.056	70.735	0.000	3.835	4.054
## 65	a5	~1		1	1	.p65.	3.562	0.062	57.403	0.000	3.440	3.684
## 66	a7	~1		1	1	.p66.	3.999	0.055	72.486	0.000	3.891	4.107
## 67	a9	~1		1	1	.p67.	3.618	0.059	61.186	0.000	3.503	3.734
## 68	c3	~1		1	1	.p68.	3.287	0.059	56.183	0.000	3.173	3.402
## 69	c4	~1		1	1	.p69.	4.263	0.039	109.524	0.000	4.187	4.339
## 70	c8	~1		1	1	.p70.	4.181	0.044	94.704	0.000	4.095	4.268
## 71	c9	~1		1	1	.p71.	3.599	0.071	50.883	0.000	3.461	3.738
## 72	e1	~1		1	1	.p72.	2.270	0.060	38.013	0.000	2.153	2.387
## 73	e4	~1		1	1	.p73.	2.924	0.071	41.218	0.000	2.785	3.063
## 74	e6	~1		1	1		3.012	0.078	38.552	0.000	2.859	3.165
## 75	e7	~1		1	1	.p75.	3.091	0.061	50.674	0.000	2.971	3.210
## 76	n1	~1		1	1		2.259	0.062	36.249	0.000	2.137	2.382
## 77	n2	~1		1	1		2.460	0.072	33.974	0.000	2.318	2.602
## 78	n6	~1		1	1	.p78.	2.324	0.058	39.856	0.000	2.209	2.438
## 79	n8	~1		1	1	.p79.	2.279	0.071	31.976	0.000	2.139	2.418
## 80	i2	~1		1	1	.p80.	3.972	0.055	72.365	0.000	3.864	4.079
## 81	i8	~1		1	1	.p81.	3.590	0.062	57.626	0.000	3.468	3.712
## 82	i9	~1		1	1	.p82.	3.615	0.061	59.144	0.000	3.495	3.735
## 83	i10	~1		1	1	.p83.	4.072	0.063	64.852	0.000	3.948	4.195
## 84	A	~1		1	1		0.000	0.000	NA	NA	0.000	0.000
## 85	C	~1		1	1		0.000	0.000	NA	NA	0.000	0.000
## 86	E	~1		1	1		0.000	0.000	NA	NA	0.000	0.000
## 87	N	~1		1	1		0.000	0.000	NA	NA	0.000	0.000
## 88	O	~1		1	1		0.000	0.000	NA	NA	0.000	0.000
## 89	A	=~	a2	2	2	.p1.	0.322	0.055	5.878	0.000	0.215	0.429
## 90	A	=~	a5	2	2	.p2.	0.655	0.060	10.841	0.000	0.537	0.773
## 91	A	=~	a7	2	2	.p3.	0.645	0.054	11.912	0.000	0.539	0.751
## 92	A	=~	a9	2	2	.p4.	0.745	0.056	13.284	0.000	0.636	0.855
## 93	C	=~	c3	2	2	.p5.	0.570	0.052	10.947	0.000	0.468	0.672
## 94	C	=~	c4	2	2	.p6.	0.341	0.049	7.037	0.000	0.246	0.436
## 95	C	=~	c8	2	2	.p7.	0.398	0.049	8.100	0.000	0.301	0.494
## 96	C	=~	c9	2	2	.p8.	0.745	0.081	9.170	0.000	0.586	0.905
## 97	E	=~	e1	2	2	.p9.	0.657	0.050	13.147	0.000	0.559	0.755
## 98	E	=~	e4	2	2	.p10.	0.803	0.069	11.594	0.000	0.667	0.939
## 99	E	=~	e6	2	2	.p11.	0.799	0.062	12.841	0.000	0.677	0.920
## 100	E	=~	e7	2	2	.p12.	0.686	0.062	10.993	0.000	0.564	0.808
## 101	N	=~	n1	2	2	.p13.	0.507	0.057	8.964	0.000	0.396	0.618

## 102	N	=~	n2	2	2	.p14.	0.824	0.063	13.080	0.000	0.701	0.948
## 103	N	=~	n6	2	2	.p15.	0.600	0.053	11.245	0.000	0.495	0.704
## 104	N	=~	n8	2	2	.p16.	0.825	0.064	12.803	0.000	0.699	0.952
## 105	0	=~	i2	2	2	.p17.	0.512	0.081	6.356	0.000	0.354	0.670
## 106	0	=~	i8	2	2	.p18.	0.425	0.080	5.344	0.000	0.269	0.581
## 107	0	=~	i9	2	2	.p19.	0.485	0.075	6.457	0.000	0.338	0.632
## 108	0	=~	i10	2	2	.p20.	0.570	0.091	6.273	0.000	0.392	0.748
## 109	a2	~~	a5	2	2		0.099	0.041	2.396	0.017	0.018	0.180
## 110	e4	~~	e7	2	2		-0.083	0.068	-1.219	0.223	-0.216	0.050
## 111	i2	~~	i10	2	2		0.275	0.101	2.722	0.006	0.077	0.474
## 112	i8	~~	i9	2	2		0.580	0.090	6.437	0.000	0.403	0.757
## 113	a9	~~	i9	2	2		-0.006	0.037	-0.148	0.882	-0.078	0.067
## 114	c3	~~	e6	2	2		-0.030	0.059	-0.506	0.613	-0.144	0.085
## 115	a2	~~	e7	2	2		-0.116	0.039	-2.980	0.003	-0.191	-0.040
## 116	e7	~~	n2	2	2		-0.146	0.053	-2.783	0.005	-0.249	-0.043
## 117	a2	~~	a2	2	2	.p29.	0.544	0.050	10.946	0.000	0.447	0.641
## 118	a5	~~	a5	2	2	.p30.	0.536	0.055	9.759	0.000	0.429	0.644
## 119	a7	~~	a7	2	2	.p31.	0.410	0.053	7.704	0.000	0.306	0.515
## 120	a9	~~	a9	2	2	.p32.	0.356	0.054	6.611	0.000	0.251	0.462
## 121	c3	~~	c3	2	2	.p33.	0.935	0.074	12.559	0.000	0.789	1.081
## 122	c4	~~	c4	2	2	.p34.	0.410	0.039	10.578	0.000	0.334	0.486
## 123	c8	~~	c8	2	2		0.705	0.093	7.606	0.000	0.523	0.886
## 124	c9	~~	c9	2	2	.p36.	0.925	0.115	8.019	0.000	0.699	1.151
## 125	e1	~~	e1	2	2	.p37.	0.784	0.058	13.555	0.000	0.671	0.898
## 126	e4	~~	e4	2	2	.p38.	0.991	0.090	11.035	0.000	0.815	1.168
## 127	e6	~~	e6	2	2	.p39.	0.881	0.073	12.136	0.000	0.739	1.023
## 128	e7	~~	e7	2	2	.p40.	0.612	0.069	8.919	0.000	0.477	0.746
## 129	n1	~~	n1	2	2		0.944	0.078	12.028	0.000	0.790	1.097
## 130	n2	~~	n2	2	2		0.959	0.116	8.259	0.000	0.731	1.186
## 131	n6	~~	n6	2	2	.p43.	0.748	0.059	12.641	0.000	0.632	0.864
## 132	n8	~~	n8	2	2	.p44.	0.652	0.075	8.691	0.000	0.505	0.799
## 133	i2	~~	i2	2	2	.p45.	0.735	0.090	8.123	0.000	0.558	0.912
## 134	i8	~~	i8	2	2	.p46.	1.182	0.094	12.529	0.000	0.997	1.367
## 135	i9	~~	i9	2	2	.p47.	1.015	0.090	11.268	0.000	0.839	1.192
## 136	i10	~~	i10	2	2	.p48.	0.786	0.122	6.449	0.000	0.547	1.024
## 137	A	~~	A	2	2		0.562	0.114	4.945	0.000	0.339	0.785
## 138	C	~~	C	2	2		1.455	0.251	5.797	0.000	0.963	1.947
## 139	E	~~	E	2	2		0.979	0.130	7.559	0.000	0.725	1.233
## 140	N	~~	N	2	2		1.114	0.167	6.657	0.000	0.786	1.442
## 141	O	~~	O	2	2		1.859	0.468	3.973	0.000	0.942	2.777
## 142	A	~~	C	2	2		-0.036	0.081	-0.443	0.658	-0.195	0.123
## 143	A	~~	E	2	2		0.135	0.065	2.093	0.036	0.009	0.262
## 144	A	~~	N	2	2		-0.159	0.078	-2.036	0.042	-0.313	-0.006
## 145	A	~~	O	2	2		0.294	0.109	2.703	0.007	0.081	0.507
## 146	C	~~	E	2	2		0.114	0.100	1.140	0.254	-0.082	0.311
## 147	C	~~	N	2	2		-0.310	0.118	-2.635	0.008	-0.541	-0.079
## 148	C	~~	O	2	2		-0.245	0.159	-1.538	0.124	-0.557	0.067
## 149	E	~~	N	2	2		-0.175	0.091	-1.929	0.054	-0.354	0.003
## 150	E	~~	O	2	2		0.455	0.137	3.308	0.001	0.185	0.724
## 151	N	~~	O	2	2		-0.055	0.131	-0.420	0.674	-0.311	0.201
## 152	a2	~1		2	2		4.098	0.063	65.328	0.000	3.975	4.221
## 153	a5	~1		2	2	.p65.	3.562	0.062	57.403	0.000	3.440	3.684
## 154	a7	~1		2	2	.p66.	3.999	0.055	72.486	0.000	3.891	4.107
## 155	a9	~1		2	2	.p67.	3.618	0.059	61.186	0.000	3.503	3.734

## 156	c3 ~1	2	2 .p68.	3.287	0.059	56.183	0.000	3.173	3.402
## 157	c4 ~1	2	2 .p69.	4.263	0.039	109.524	0.000	4.187	4.339
## 158	c8 ~1	2	2 .p70.	4.181	0.044	94.704	0.000	4.095	4.268
## 159	c9 ~1	2	2 .p71.	3.599	0.071	50.883	0.000	3.461	3.738
## 160	e1 ~1	2	2 .p72.	2.270	0.060	38.013	0.000	2.153	2.387
## 161	e4 ~1	2	2 .p73.	2.924	0.071	41.218	0.000	2.785	3.063
## 162	e6 ~1	2	2	3.428	0.089	38.528	0.000	3.253	3.602
## 163	e7 ~1	2	2 .p75.	3.091	0.061	50.674	0.000	2.971	3.210
## 164	n1 ~1	2	2	2.566	0.071	35.974	0.000	2.427	2.706
## 165	n2 ~1	2	2	2.699	0.094	28.652	0.000	2.515	2.884
## 166	n6 ~1	2	2 .p78.	2.324	0.058	39.856	0.000	2.209	2.438
## 167	n8 ~1	2	2 .p79.	2.279	0.071	31.976	0.000	2.139	2.418
## 168	i2 ~1	2	2 .p80.	3.972	0.055	72.365	0.000	3.864	4.079
## 169	i8 ~1	2	2 .p81.	3.590	0.062	57.626	0.000	3.468	3.712
## 170	i9 ~1	2	2 .p82.	3.615	0.061	59.144	0.000	3.495	3.735
## 171	i10 ~1	2	2 .p83.	4.072	0.063	64.852	0.000	3.948	4.195
## 172	A ~1	2	2	0.743	0.083	8.936	0.000	0.580	0.905
## 173	C ~1	2	2	0.140	0.115	1.219	0.223	-0.085	0.366
## 174	E ~1	2	2	-0.019	0.104	-0.186	0.853	-0.224	0.185
## 175	N ~1	2	2	-0.049	0.111	-0.444	0.657	-0.266	0.168
## 176	O ~1	2	2	-0.458	0.166	-2.764	0.006	-0.783	-0.133