

# COS-D419 Factor Analysis and Structural Equation Models 2023, Assignment 4

Rong Guang

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## 1 SEM & teacher burnout

### 1.1 Exercise 4.1

Draw the graph of the initial, full structural equation model. Make sure that you have included all the specified paths.

Estimate the initial model using the robust MLM estimator (*robust variant of the ML estimator, to be precise!*) and present a brief summary of the model fit.

## 2 Preparation

### 2.1 Read in the data set

Start by downloading the data file from Moodle to Project folder.

```
library(tidyverse)
library(readr)
library(here)
```

```
#This week's file name
latest.name <- "ALLSEC.CSV"

#read in the data
mbi <- read_csv(file.path(here(),
                           'data',
                           latest.name))
```

## 2.2 Write functions

To control length of reports, codes already shown in the previous homework were not showing in the current report. Yet they are available in .rmd report.

**2.2.1 to check unique values**

**2.2.2 to generate CFA results with improved readability**

**2.2.3 to generate functions for improving aesthetics of correlation matrix**

**2.2.4 to generate a function for histogram overlapping with density plot**

**2.2.5 to generate a function for violin overlapping with box plot**

**2.2.6 To generate a function describing continuous data set**

## 2.3 Inspect the data

### 2.3.1 Data structure

Have a quick overview of the data structure

```
library(knitr)
library(broom)
dim(mbi);mbi %>% apply(2, function(x)class(x));
```

```
## [1] 1430 32
```

```
##      ROLEA1      ROLEA2      ROLEC1      ROLEC2      WORK1      WORK2      CCLIM1      CCLIM2
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##      CCLIM3      CCLIM4      DEC1      DEC2      SSUP1      SSUP2      PSUP1      PSUP2
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##      SELF1      SELF2      SELF3      ELC1      ELC2      ELC3      ELC4      ELC5
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##      EE1      EE2      EE3      DP1      DP2      PA1      PA2      PA3
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
```

The data set contains 22 numeric variables of 372 obs. Their values appear to follow a consistent pattern covering the integer from 1 to 7, except for Items 4, 7, 17 and 21, which did not include a value of 1.

### 2.3.2 Descriptive statistics of measured variables

```
library(finalfit);library(kableExtra);

descriptive(mbi) |>
  pack_rows(index =
    c("Factor 1*: Role Ambiguity \n(high score means negative)" = 2,
      "Factor 2*: Role conflict \n(high score means negative)" = 2,
      "Factor 3*: Work overload \n(high score means negative)" = 2,
      "Factor 4‡: classroom climate" = 4,
      "Factor 5*: Decision-making" = 2,
      "Factor 6*: Superior support" = 2,
      "Factor 7*: Peer support" = 2,
      "Factor 8‡: Self-esteem" = 3,
      "Factor 9‡: External locus of control" = 5,
      "Factor 10‡: Emotional Exhaustion \n(high score means negative)" = 3,
      "Factor 11‡: Depersonalization \n(high score means negative)" = 2,
      "Factor 12‡: Personal Accomplishment" = 3)) |>
  footnote(general =
    "Indicators variables were formulated through item parcels.",
    symbol = c("These indicators are parcels from Teacher Stress Scale instrument",
      "These indicators are parcels from BMI instrument",
      "These parcels consist of items from single unidimensional scales")
  )
```

Table 1: Descriptive statistics for measurements

	n	n of NA	Central tendency		Dispersion tendency			
			Mean	Median	SD	Min	Max	Q1~Q3
Factor 1*: Role Ambiguity (high score means negative)								
ROLEA1	1430	0	2.4	2.3	0.9	1.0	6.0	1.7 ~ 3.0
ROLEA2	1430	0	2.1	2.0	1.0	1.0	6.0	1.5 ~ 2.5
Factor 2*: Role conflict (high score means negative)								
ROLEC1	1430	0	3.0	3.0	1.1	1.0	6.0	2.3 ~ 3.7
ROLEC2	1430	0	3.0	3.0	1.2	1.0	6.0	2.0 ~ 4.0
Factor 3*: Work overload (high score means negative)								
WORK1	1430	0	3.2	3.3	1.2	1.0	6.0	2.3 ~ 4.0
WORK2	1430	0	2.2	2.0	1.1	1.0	6.0	1.5 ~ 3.0
Factor 4‡: classroom climate								
CCLIM1	1430	0	3.0	3.0	0.5	1.0	4.0	2.7 ~ 3.3
CCLIM2	1430	0	2.7	2.7	0.6	1.0	4.0	2.3 ~ 3.0
CCLIM3	1430	0	2.9	3.0	0.5	1.0	4.0	2.7 ~ 3.3
CCLIM4	1430	0	3.1	3.0	0.7	1.0	4.0	2.5 ~ 3.5
Factor 5*: Decision-making								
DEC1	1430	0	4.0	4.0	1.0	1.0	6.0	3.3 ~ 4.7
DEC2	1430	0	4.2	4.5	1.3	1.0	6.0	3.5 ~ 5.5
Factor 6*: Superior support								

Table 1: Descriptive statistics for measurements (*continued*)

	n	n of NA	Central tendency		Dispersion tendency			
			Mean	Median	SD	Min	Max	Q1~Q3
SSUP1	1430	0	4.3	4.3	1.2	1.0	6.0	3.7 ~ 5.3
SSUP2	1430	0	4.4	4.5	1.3	1.0	6.0	3.5 ~ 5.5
<b>Factor 7*: Peer support</b>								
PSUP1	1430	0	4.6	4.7	1.0	1.0	6.0	4.0 ~ 5.3
PSUP2	1430	0	4.6	4.5	0.9	1.0	6.0	4.0 ~ 5.0
<b>Factor 8†: Self-esteem</b>								
SELF1	1430	0	3.6	3.7	0.4	1.0	4.0	3.3 ~ 4.0
SELF2	1430	0	3.6	3.8	0.5	1.0	4.0	3.4 ~ 4.0
SELF3	1430	0	3.5	3.7	0.5	1.0	4.0	3.3 ~ 4.0
<b>Factor 9‡: External locus of control</b>								
ELC1	1430	0	2.9	3.0	0.6	1.0	4.8	2.6 ~ 3.4
ELC2	1430	0	3.0	3.0	0.6	1.0	5.0	2.5 ~ 3.5
ELC3	1430	0	2.8	2.8	0.5	1.0	4.8	2.4 ~ 3.2
ELC4	1430	0	2.2	2.2	0.6	1.0	4.5	1.8 ~ 2.5
ELC5	1430	0	2.5	2.4	0.6	1.0	4.8	2.0 ~ 3.0
<b>Factor 10†: Emotional Exhaustion (high score means negative)</b>								
EE1	1430	0	3.9	4.0	1.3	1.0	7.0	3.0 ~ 4.7
EE2	1430	0	3.5	3.3	1.3	1.0	7.0	2.7 ~ 4.3
EE3	1430	0	3.2	3.0	1.3	1.0	7.0	2.0 ~ 4.0
<b>Factor 11†: Depersonalization (high score means negative)</b>								
DP1	1430	0	2.3	2.0	1.1	1.0	6.7	1.3 ~ 3.0
DP2	1430	0	2.1	1.5	1.2	1.0	7.0	1.0 ~ 2.5
<b>Factor 12‡: Personal Accomplishment</b>								
PA1	1430	0	5.7	6.0	0.9	2.0	7.0	5.3 ~ 6.3
PA2	1430	0	5.8	6.0	1.0	2.0	7.0	5.5 ~ 6.5
PA3	1430	0	5.8	6.0	1.0	2.0	7.0	5.3 ~ 6.7

*Note:*

Indicators variables were formulated through item parcels.

\* These indicators are parcels from Teacher Stress Scale instrument

† These indicators are parcels from BMI instrument

‡ These parcels consist of items from single unidimensional scales

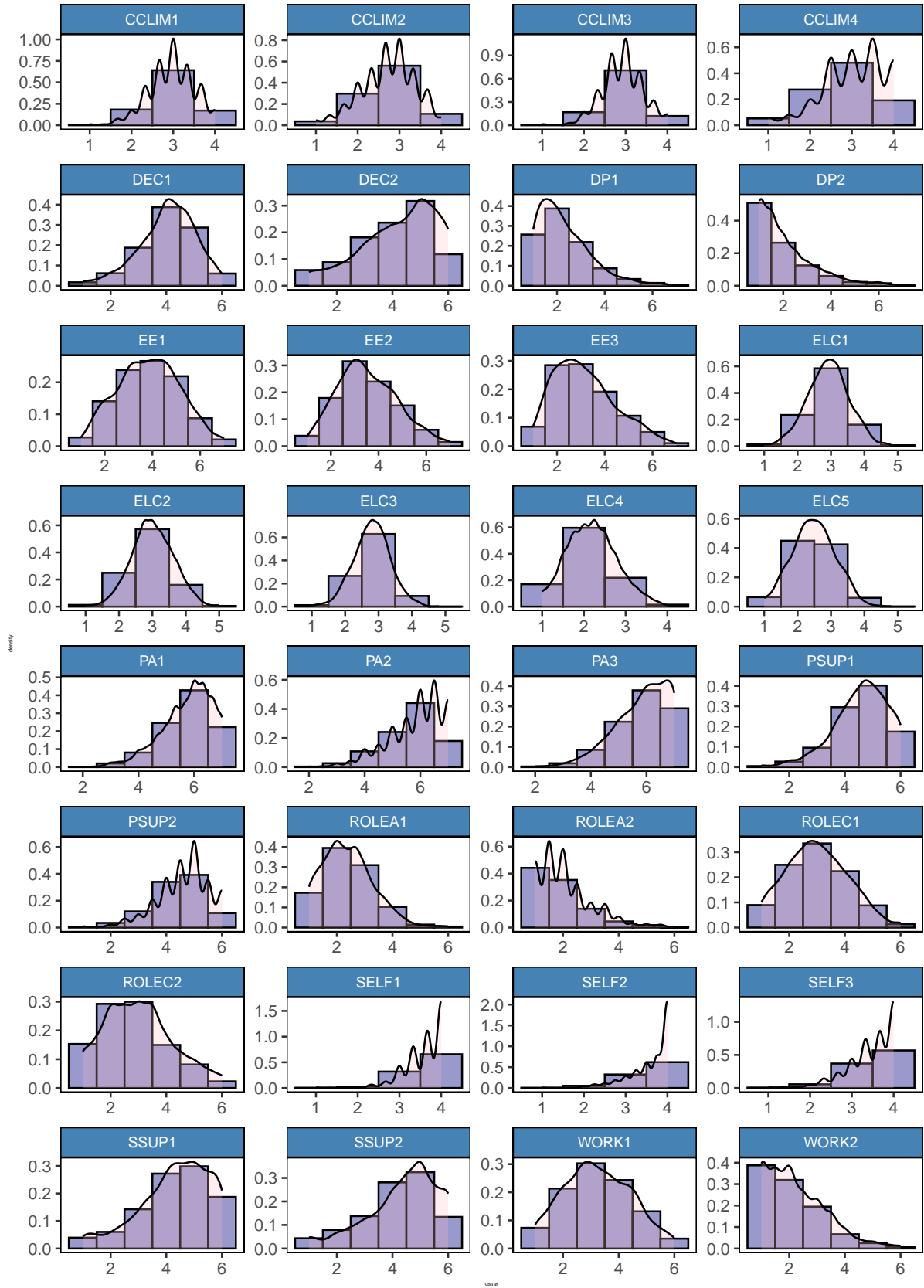
### 2.3.3 Visualization

(1) Histogram

Distribution of the data was examined via Histogram

```
corr.density(mbi, fig.num = 1)
```

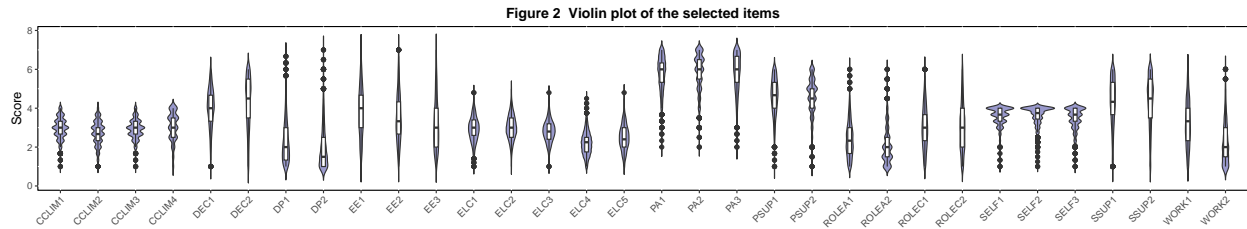
**Figure 1 Distribution of selected items**



## (2) Violin plot

Violin plot also provides information on distribution, plus ideas on out-liers.

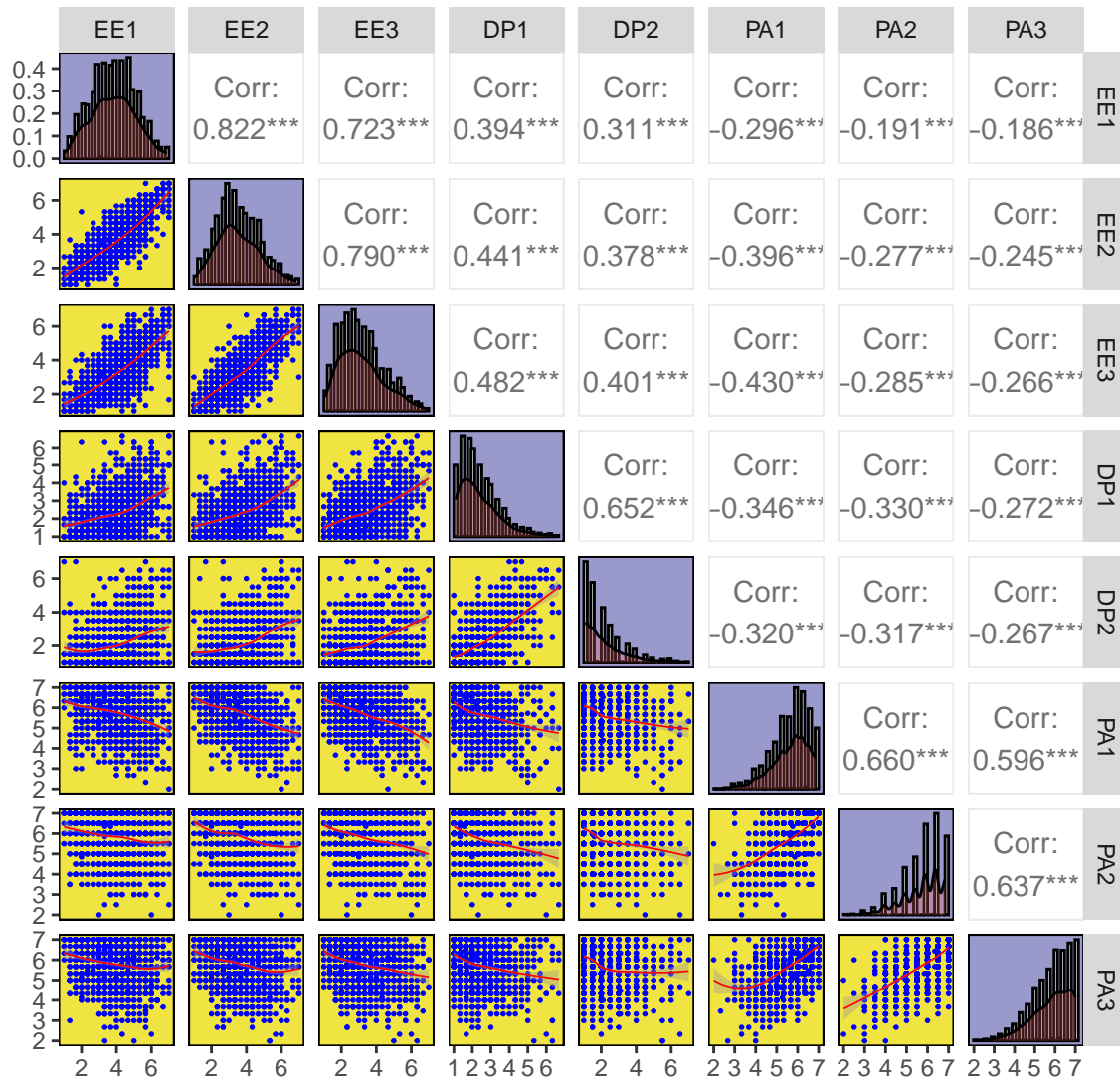
```
violin.box(mbi, fig.num = 2)
```



## (3) Correlation among items

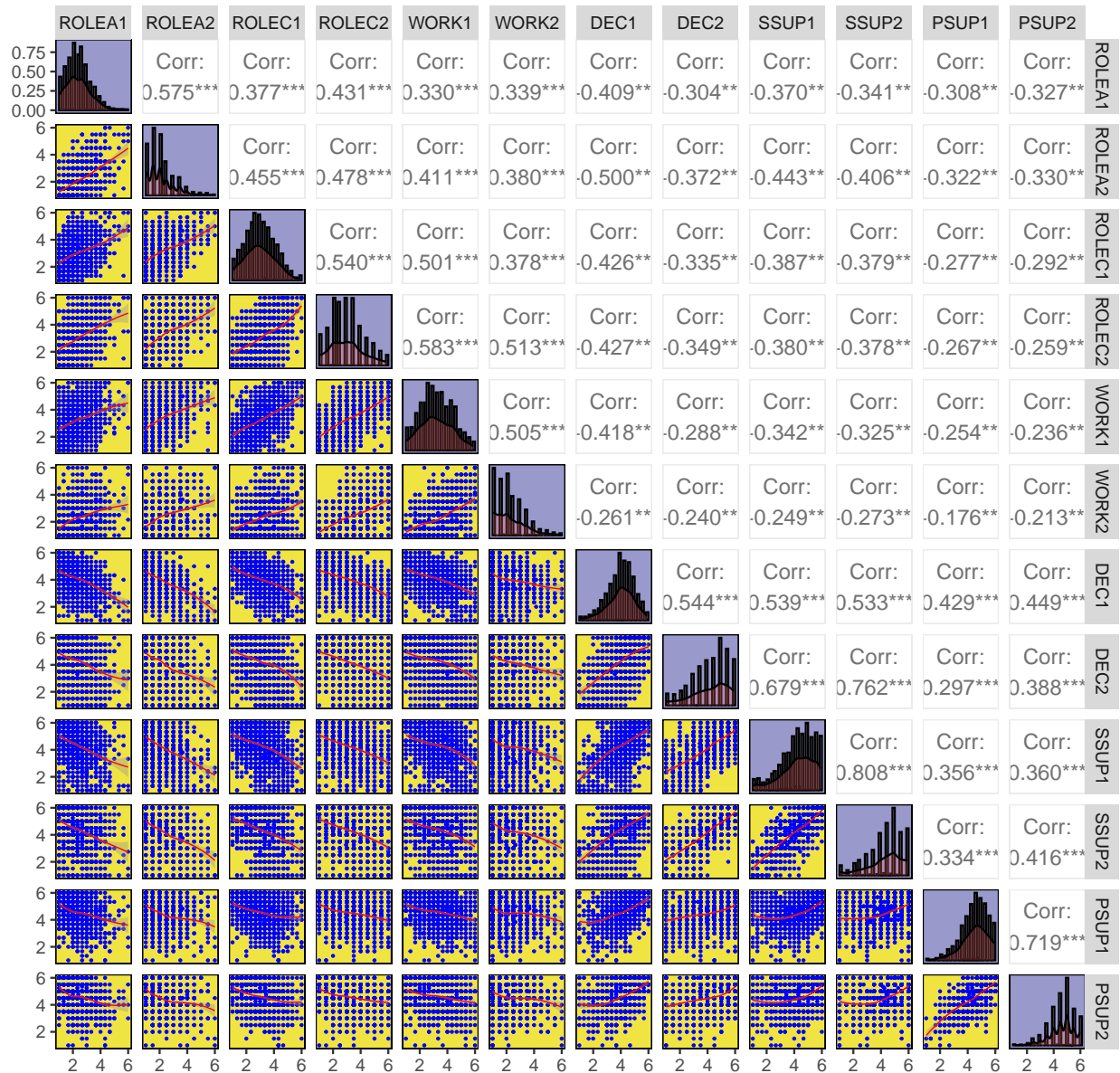
```
#draw it
mbi |> select(starts_with("EE")|starts_with("DP")|starts_with("PA")) |>
  ggpairs(lower =
    list(continuous = my.fun.smooth), #lower half show points with fitted line
    diag =
      list(continuous = my.fun.density), #diagonal grids show density plots
      title = "Fig3(a). Relationships among parcels of MBI instrument") + #title
  theme (plot.title = element_text(size = 11, #adjust title visuals
    face = "bold"))
```

**Fig3(a). Relationships among parcels of MBI instrument**



```
mbi |> select(starts_with("ROL")|starts_with("WOR")|starts_with("DEC")|contains("SUP")) |>
ggpairs(lower =
  list(continuous = my.fun.smooth), #lower half show points with fitted line
  diag =
    list(continuous = my.fun.density), #diagonal grids show density plots
  title = "Fig3(b). Relationships among parcels of TSS instrument") + #title
theme (plot.title = element_text(size = 15, #adjust title visuals
  face = "bold"))
```

**Fig3(b). Relationships among parcels of TSS instrument**



### 2.3.4 Define the initial, full structural equation model and visualize it:

Here's an example of how to draw the model before estimating it. Feel free to modify the R code!

**OBS!** I have given the model syntax below using *numeric names* for the factors (F1, F2 etc.), thus following Byrne's book. However, that is NOT the best practice, so you might consider changing those names. (It might make your task somewhat easier...)

```
library(semPlot)#install.packages("semPlot")

initial_model <- '
# Factors:
F1ROLA =~ ROLEA1 + ROLEA2 + DEC2
```



```

F2ROLC =~ ROLEC1 + ROLEC2
F3WORK =~ WORK1 + WORK2
F4CLIM =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F5DEC =~ DEC1 + DEC2
F6SSUP =~ SSUP1 + SSUP2 + DEC2
F7PSUP =~ PSUP1 + PSUP2
F8SELF =~ SELF1 + SELF2 + SELF3
F9ELC =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F10EE =~ EE1 + EE2 + EE3
F11DP =~ DP1 + DP2
F12PA =~ PA1 + PA2 + PA3
# Regressions:
F8SELF ~ F5DEC + F6SSUP + F7PSUP
F9ELC ~ F5DEC
F10EE ~ F2ROLC + F3WORK + F4CLIM
F11DP ~ F2ROLC + F10EE
F12PA ~ F1ROLA + F8SELF + F9ELC + F10EE + F11DP

```

```

m <- matrix(NA, 60, 72)
m[12, 68] <- "F1ROLA"
m[12, 40] <- "F2ROLC"
m[12, 28] <- "F3WORK"
m[12, 12] <- "F4CLIM"
m[21, 12] <- "F5DEC"
m[40, 12] <- "F6SSUP"
m[53, 9] <- "F7PSUP"
m[44, 24] <- "F8SELF"
m[52, 40] <- "F9ELC"
m[37, 48] <- "F10EE"
m[26, 60] <- "F11DP"
m[48, 64] <- "F12PA"

m[4, 72] <- "ROLEA1"
m[4, 64] <- "ROLEA2"
m[4, 48] <- "ROLEC1"
m[4, 40] <- "ROLEC2"
m[4, 32] <- "WORK1"
m[4, 24] <- "WORK2"
m[4, 16] <- "CCLIM1"
m[5, 10] <- "CCLIM2"
m[10, 4] <- "CCLIM3"
m[15, 4] <- "CCLIM4"
m[20, 4] <- "DEC1"
m[27, 6] <- "DEC2"
m[36, 4] <- "SSUP1"
m[40, 4] <- "SSUP2"
m[59, 6] <- "PSUP1"
m[59, 13] <- "PSUP2"
m[48, 32] <- "SELF1"
m[52, 28] <- "SELF2"
m[51, 21] <- "SELF3"
m[56, 50] <- "ELC1"

```

```

m[60, 48] <- "ELC2"
m[60, 42] <- "ELC3"
m[60, 35] <- "ELC4"
m[56, 31] <- "ELC5"
m[43, 45] <- "EE1"
m[39, 40] <- "EE2"
m[35, 38] <- "EE3"
m[20, 64] <- "DP1"
m[20, 58] <- "DP2"
m[52, 71] <- "PA1"
m[56, 64] <- "PA2"
m[53, 57] <- "PA3"

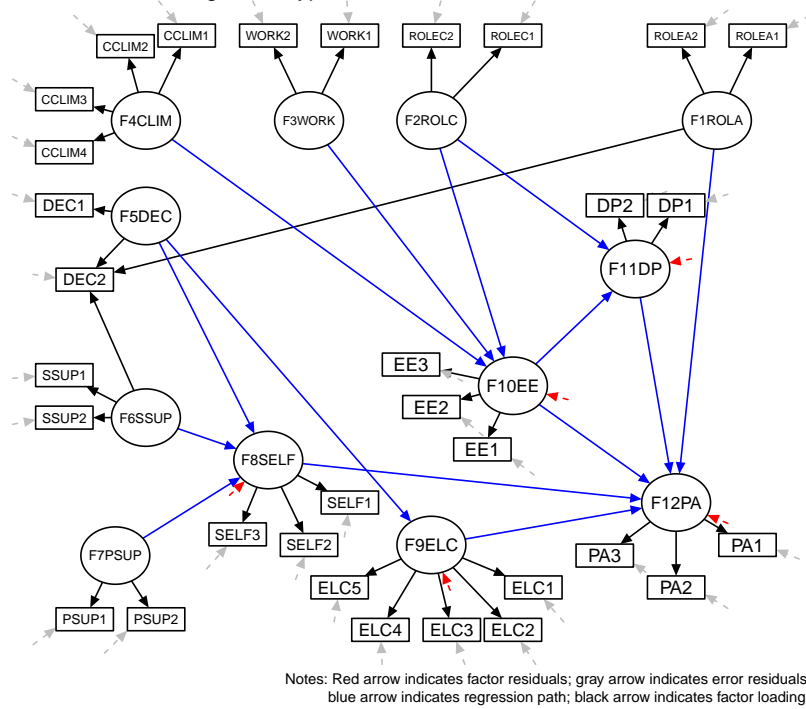
```

```

semPaths(semPlotModel(initial_model),
         style = "lisrel",
         rotation = 2,
         sizeLat = 6,
         sizeLat2 = 5,
         sizeMan = 5,
         sizeMan2 = 2,
         residScale = 4,
         shapeMan = "rectangle",
         edge.color = c(rep("black",34),
                        rep("blue",14),
                        rep("gray",32),
                        rep("red",5)),
         residuals = T,
         layout = m,
         nCharNodes=0,
         optimizeLatRes = T,
         exoVar = F)
title(main = list("Figure 1. Hypothesized model of teacher burnout", cex = 1.5, font =1),
      outer = F, line = -2)
title(sub = "Notes: Red arrow indicates factor residuals; gray arrow indicates error residuals;
          blue arrow indicates regression path; black arrow indicates factor loading", line = 0, adj = 0.7)

```

Figure 1. Hypothesized model of teacher burnout



### 2.3.5 Estimate the SEM model:

*Note:* Here, we will use the `sem()` function for the estimation, instead of the `cfa()` function, as we are now working with a full SEM (i.e., CFA + regression paths).

```
library(lavaan)

modell1 <- initial_model # defined above

# Estimate the model with the robust (MLM) estimator:
sem1 <- sem(modell1, data = mbi, estimator = "MLM")

# Numerical summary of the model:
summary(sem1, fit.measures = TRUE, standardized = TRUE)
```

```
## lavaan 0.6.13 ended normally after 205 iterations
##
## Estimator ML
## Optimization method NLMINB
## Number of model parameters 101
##
## Number of observations 1430
##
## Model Test User Model:
```

##		Standard	Scaled
##	Test Statistic	1737.090	1541.844
##	Degrees of freedom	427	427
##	P-value (Chi-square)	0.000	0.000
##	Scaling correction factor		1.127
##	Satorra-Bentler correction		
##			
##	Model Test Baseline Model:		
##			
##	Test statistic	23532.624	19072.057
##	Degrees of freedom	496	496
##	P-value	0.000	0.000
##	Scaling correction factor		1.234
##			
##	User Model versus Baseline Model:		
##			
##	Comparative Fit Index (CFI)	0.943	0.940
##	Tucker-Lewis Index (TLI)	0.934	0.930
##			
##	Robust Comparative Fit Index (CFI)		0.945
##	Robust Tucker-Lewis Index (TLI)		0.936
##			
##	Loglikelihood and Information Criteria:		
##			
##	Loglikelihood user model (H0)	-47240.128	-47240.128
##	Loglikelihood unrestricted model (H1)	-46371.583	-46371.583
##			
##	Akaike (AIC)	94682.256	94682.256
##	Bayesian (BIC)	95214.064	95214.064
##	Sample-size adjusted Bayesian (SABIC)	94893.222	94893.222
##			
##	Root Mean Square Error of Approximation:		
##			
##	RMSEA	0.046	0.043
##	90 Percent confidence interval - lower	0.044	0.041
##	90 Percent confidence interval - upper	0.049	0.045
##	P-value H_0: RMSEA <= 0.050	0.996	1.000
##	P-value H_0: RMSEA >= 0.080	0.000	0.000
##			
##	Robust RMSEA		0.045
##	90 Percent confidence interval - lower		0.043
##	90 Percent confidence interval - upper		0.048
##	P-value H_0: Robust RMSEA <= 0.050		0.999
##	P-value H_0: Robust RMSEA >= 0.080		0.000
##			
##	Standardized Root Mean Square Residual:		
##			
##	SRMR	0.053	0.053
##			
##	Parameter Estimates:		
##			
##	Standard errors	Robust.sem	
##	Information	Expected	
##	Information saturated (h1) model	Structured	

```

##
## Latent Variables:
##      Estimate   Std.Err   z-value   P(>|z|)   Std.lv   Std.all
## F1ROLA =~
##   ROLEA1       1.000
##   ROLEA2       1.238   0.058   21.499   0.000   0.643   0.703
##   DEC2         0.229   0.089    2.579   0.010   0.147   0.111
## F2ROLC =~
##   ROLEC1       1.000
##   ROLEC2       1.308   0.053   24.767   0.000   0.755   0.686
##   0.988   0.801
## F3WORK =~
##   WORK1        1.000
##   WORK2        0.749   0.032   23.203   0.000   0.893   0.743
##   0.669   0.614
## F4CLIM =~
##   CCLIM1       1.000
##   CCLIM2       1.478   0.077   19.254   0.000   0.334   0.618
##   CCLIM3       0.958   0.056   17.114   0.000   0.494   0.786
##   CCLIM4       0.320   0.649
##   1.334   0.080   16.764   0.000   0.320   0.649
##   0.446   0.609
## F5DEC =~
##   DEC1         1.000
##   DEC2         0.407   0.106    3.852   0.000   0.710   0.703
##   0.289   0.218
## F6SSUP =~
##   SSUP1        1.000
##   SSUP2        1.098   0.026   42.261   0.000   1.073   0.862
##   DEC2         0.859   0.049   17.574   0.000   1.178   0.935
##   0.921   0.694
## F7PSUP =~
##   PSUP1        1.000
##   PSUP2        1.079   0.046   23.684   0.000   1.073   0.862
##   0.771   0.800
##   0.833   0.899
## F8SELF =~
##   SELF1        1.000
##   SELF2        1.278   0.045   28.157   0.000   0.771   0.800
##   SELF3        1.357   0.057   23.744   0.000   0.833   0.899
##   0.462   0.848
## F9ELC =~
##   ELC1         1.000
##   ELC2         0.848   0.042   20.398   0.000   0.340   0.765
##   ELC3         0.944   0.041   23.153   0.000   0.435   0.863
##   ELC4         0.904   0.047   19.274   0.000   0.462   0.848
##   ELC5         1.110   0.050   22.388   0.000   0.340   0.765
##   0.430   0.690
##   0.365   0.582
##   0.406   0.741
##   0.389   0.643
##   0.477   0.741
## F10EE =~
##   EE1          1.000
##   EE2          1.020   0.019   53.502   0.000   0.430   0.690
##   EE3          0.973   0.023   43.048   0.000   0.365   0.582
##   1.141   0.871
##   1.164   0.926
##   1.111   0.856
## F11DP =~
##   DP1          1.000
##   DP2          0.918   0.046   20.022   0.000   1.141   0.871
##   0.959   0.876
##   0.880   0.745
## F12PA =~
##   PA1          1.000
##   PA2          1.039   0.038   27.420   0.000   0.959   0.876
##   PA3          0.963   0.040   23.869   0.000   0.880   0.745
##   0.742   0.819
##   0.771   0.807
##   0.715   0.746
##
## Regressions:
##      Estimate   Std.Err   z-value   P(>|z|)   Std.lv   Std.all
## F8SELF ~
##   F5DEC         0.475   0.054    8.784   0.000   0.742   0.819
##   0.771   0.807
##   0.715   0.746

```

##	F6SSUP	-0.155	0.026	-5.890	0.000	-0.490	-0.490
##	F7PSUP	-0.066	0.030	-2.223	0.026	-0.150	-0.150
##	F9ELC ~						
##	F5DEC	-0.288	0.023	-12.787	0.000	-0.476	-0.476
##	F10EE ~						
##	F2ROLC	-8.707	6.705	-1.298	0.194	-5.765	-5.765
##	F3WORK	8.082	5.647	1.431	0.152	6.325	6.325
##	F4CLIM	-0.930	0.740	-1.257	0.209	-0.272	-0.272
##	F11DP ~						
##	F2ROLC	0.258	0.054	4.789	0.000	0.203	0.203
##	F10EE	0.373	0.036	10.242	0.000	0.444	0.444
##	F12PA ~						
##	F1ROLA	-0.071	0.048	-1.474	0.140	-0.062	-0.062
##	F8SELF	0.472	0.090	5.245	0.000	0.217	0.217
##	F9ELC	-0.208	0.052	-3.975	0.000	-0.121	-0.121
##	F10EE	-0.064	0.026	-2.416	0.016	-0.098	-0.098
##	F11DP	-0.218	0.033	-6.556	0.000	-0.281	-0.281
##							
##	Covariances:						
##		Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
##	F1ROLA ~~						
##	F2ROLC	0.360	0.025	14.389	0.000	0.742	0.742
##	F3WORK	0.419	0.027	15.239	0.000	0.730	0.730
##	F4CLIM	-0.065	0.008	-7.755	0.000	-0.304	-0.304
##	F5DEC	-0.373	0.026	-14.497	0.000	-0.817	-0.817
##	F6SSUP	-0.386	0.030	-12.736	0.000	-0.560	-0.560
##	F7PSUP	-0.242	0.022	-10.976	0.000	-0.488	-0.488
##	F2ROLC ~~						
##	F3WORK	0.666	0.035	19.038	0.000	0.988	0.988
##	F4CLIM	-0.086	0.011	-8.092	0.000	-0.340	-0.340
##	F5DEC	-0.407	0.028	-14.531	0.000	-0.759	-0.759
##	F6SSUP	-0.429	0.032	-13.235	0.000	-0.529	-0.529
##	F7PSUP	-0.234	0.023	-10.351	0.000	-0.402	-0.402
##	F3WORK ~~						
##	F4CLIM	-0.097	0.013	-7.504	0.000	-0.326	-0.326
##	F5DEC	-0.491	0.030	-16.117	0.000	-0.775	-0.775
##	F6SSUP	-0.501	0.035	-14.309	0.000	-0.523	-0.523
##	F7PSUP	-0.277	0.026	-10.790	0.000	-0.403	-0.403
##	F4CLIM ~~						
##	F5DEC	0.100	0.011	9.329	0.000	0.421	0.421
##	F6SSUP	0.120	0.014	8.728	0.000	0.335	0.335
##	F7PSUP	0.055	0.009	5.897	0.000	0.212	0.212
##	F5DEC ~~						
##	F6SSUP	0.616	0.038	16.239	0.000	0.810	0.810
##	F7PSUP	0.385	0.028	13.835	0.000	0.704	0.704
##	F6SSUP ~~						
##	F7PSUP	0.394	0.032	12.431	0.000	0.476	0.476
##							
##	Variances:						
##		Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
##	.ROLEA1	0.422	0.024	17.386	0.000	0.422	0.505
##	.ROLEA2	0.313	0.027	11.556	0.000	0.313	0.331
##	.DEC2	0.598	0.033	18.016	0.000	0.598	0.339
##	.ROLEC1	0.642	0.029	22.304	0.000	0.642	0.530

##	.ROLEC2	0.546	0.037	14.798	0.000	0.546	0.359
##	.WORK1	0.646	0.030	21.317	0.000	0.646	0.448
##	.WORK2	0.739	0.035	20.903	0.000	0.739	0.623
##	.CCLIM1	0.180	0.008	22.588	0.000	0.180	0.618
##	.CCLIM2	0.151	0.010	14.874	0.000	0.151	0.382
##	.CCLIM3	0.141	0.007	19.356	0.000	0.141	0.579
##	.CCLIM4	0.337	0.015	21.843	0.000	0.337	0.629
##	.DEC1	0.515	0.027	19.233	0.000	0.515	0.505
##	.SSUP1	0.398	0.026	15.205	0.000	0.398	0.257
##	.SSUP2	0.200	0.022	8.898	0.000	0.200	0.126
##	.PSUP1	0.336	0.027	12.238	0.000	0.336	0.361
##	.PSUP2	0.164	0.026	6.287	0.000	0.164	0.191
##	.SELF1	0.082	0.005	16.563	0.000	0.082	0.415
##	.SELF2	0.065	0.005	13.033	0.000	0.065	0.256
##	.SELF3	0.083	0.006	13.021	0.000	0.083	0.281
##	.ELC1	0.204	0.010	20.506	0.000	0.204	0.524
##	.ELC2	0.259	0.011	23.326	0.000	0.259	0.661
##	.ELC3	0.135	0.007	18.174	0.000	0.135	0.451
##	.ELC4	0.215	0.010	21.720	0.000	0.215	0.587
##	.ELC5	0.187	0.010	18.595	0.000	0.187	0.451
##	.EE1	0.413	0.024	17.250	0.000	0.413	0.241
##	.EE2	0.225	0.019	11.753	0.000	0.225	0.142
##	.EE3	0.449	0.025	17.799	0.000	0.449	0.267
##	.DP1	0.278	0.045	6.145	0.000	0.278	0.232
##	.DP2	0.622	0.049	12.655	0.000	0.622	0.445
##	.PA1	0.270	0.022	12.414	0.000	0.270	0.329
##	.PA2	0.319	0.025	12.783	0.000	0.319	0.349
##	.PA3	0.407	0.024	17.000	0.000	0.407	0.443
##	F1ROLA	0.413	0.033	12.434	0.000	1.000	1.000
##	F2ROLC	0.571	0.041	13.844	0.000	1.000	1.000
##	F3WORK	0.797	0.047	16.926	0.000	1.000	1.000
##	F4CLIM	0.112	0.010	10.732	0.000	1.000	1.000
##	F5DEC	0.504	0.038	13.435	0.000	1.000	1.000
##	F6SSUP	1.151	0.061	18.983	0.000	1.000	1.000
##	F7PSUP	0.595	0.043	13.894	0.000	1.000	1.000
##	.F8SELF	0.079	0.008	9.693	0.000	0.682	0.682
##	.F9ELC	0.143	0.012	12.447	0.000	0.774	0.774
##	.F10EE	-0.432	0.816	-0.530	0.596	-0.332	-0.332
##	.F11DP	0.605	0.053	11.482	0.000	0.658	0.658
##	.F12PA	0.383	0.025	15.337	0.000	0.695	0.695

## 2.4 Exercise 4.2

Proceed **step by step** following the guidelines given in the lecture material, i.e., implement the modifications **one at a time**, testing and studying each step. See (and report) how the fit improves and which parameters are suggested to be modified. Please be careful! There will (always) be a lot of suggestions... Do not list all the MIs (only a few of them are useful!), try to keep your report as concise as possible.

*Note:* A good way to proceed is to collect the necessary information (i.e., which parameter was modified and how, MI, EPC, chi-square, df, CFI, TLI, scaling correction factor, RMSEA, and SRMR) of each modelling step to a **table** (in a way or another). (Some examples in R code were given in Assignment 3, consult also the reports by other students, if you do not know how to proceed.) **Such tables makes it easy to see how the results of the modelling develop through each step.**

The best practice is to build the tables step by step: In the first table you will have only one row, then two rows, then three rows etc., and in the final version of the table you will have all the steps collected together on  $k$  rows, representing the  $k$  steps of the modelling process.

### 2.4.1 Calculating the MLM $\chi^2$ difference tests

Calculate the MLM  $\chi^2$  difference tests between the consecutive models of the above steps, as advised in the lecture material (p.14-15). Do those calculations in detail at least once or twice so that you get the idea.

*Note:* The formulas are simpler than they are in Byrne's book (p.168-169), where both MLM and ML estimations are needed. For more information, see: <https://statmodel.com/chidiff.shtml>.

For the calculations, you may use R (of course!) or Excel, or some ready-made calculation forms found on the web, such as <https://www.thestatisticalmind.com/calculators/SBChiSquareDifferenceTest.htm>.

```
# (copy and modify the R codes given earlier)
```

## 2.5 Exercise 4.3

Draw the graph of the final model and present its fit indices and the essential, standardized parameter estimates. **Pay attention to the factor correlations.**

Compare the initial and final graphs and make sure that you understand the whole modelling process and the final conclusions.

```
# (copy and modify the R codes given earlier)
```