Structural Equation Modelling: Public Trust in French Government

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Introduction

Public trust in government has always been an interesting field of study for political science scholars as well as public administration. Literature from different disciplines proved that citizen trust is key for a government to function well. From improving communication to reducing conflicts within a country, we can say trust is definitely something any government wants to earn from its citizens (Cooper, Christopher A., et al. "The Importance of Trust in Government for Public Administration: The Case of Zoning. 2008").

The aim of this paper is to try to measure overall public trust in French Government after Emmanuel Macron has been elected the 7 May 2017 to be the new French president, and also to find what could cause it to change. This topic is interesting because trust in government has always been an issue in France, as both left and right political parties got their chance to govern the country in the past, but always were seen as disappointment by the French majority. In order to earn French people trust during the presidential elections at a time when French citizens didn't trust any political parties that were there since the beginning, Macron claimed to not identity himself to a specific party, but rather as a healthy unification of both parties.

Research Questions

Trust in government is not measured the same way in all countries, and it is why our theoretical framework will be thoroughly explored before going through the analysis. First, it is important to discern trust in government and good governance. As there might be some correlation between those two concepts, if there is trust, it doesn't necessarily mean that government is functioning in a way that would be universally described as good governance. Trust means that the government is perceived to function in a way that is preferred by citizens, which is subjective. For this reason, we will use satisfaction indicators for our measurement model, as a way to measure overall trust in French government. The satisfaction indicators that we will use measure economic state of France, health services, state of democracy, and education.

On the other hand, we will introduce quality of life. We define quality of life (QOL) as an individual perception of position in their life in the context and culture of where they life, in relation to their expectations. We will measure quality of life in France by standards indicators such as income, health, social life (Benamouzig, Daniel. ≪ Mesures de qualité de vie en santé. Un processus social de subjectivation? ≫, Les Cahiers du Centre Georges Canguilhem, 2010), but also safety. The reason why we add safety as a potential good indicator of QOL, is that safety has been a growing issue in France these years, whether it is fear of terrorist attack or violent incivilities. 90 percent of french people blame the government for this issue ("Les Français et les enjeux de sécurité", Ifop pour Synopia, 2017).

The first goal of our analysis is to test whether our items indeed measure trust and quality of life, and to examine the fit of our measurement model. Next, we want to test how well does quality of life explains trust in government. Then, we will do a multigroup analysis, to see how our our parameters estimates vary between male and female.

Dataset

The dataset used for our paper is the European Social Survey ESS9-2018 and was released the 17th of February 2021. The analysis is restricted to the French case. Each line in the dataset represents a French respondent.

Codebook:

STFECO How satisfied are you with the present state of the economy in France? (0 Extremely dissatisfied - 10 Extremely satisfied)
STFDEM How satisfied are you with the way democracy works in France? (0 Extremely dissatisfied - 10 Extremely satisfied)
STFEDU What do you think overall about the state of education in France nowadays? (0 Extremely bad - 10 Extremely good)
STFHLTH What do you think overall about the state of health services in France nowadays? (0 Extremely bad - 10 Extremely good)
HEALTH How is your health in general? (1 Very good - 5 Very bad)
SCLMEET How often do you meet socially with friends, relatives or work colleagues? (1 Never - 7 Every day)
HINCTNTA Household's total net income, all sources (Deciles of the actual household income range in Belgium)
AESFDRK How safe do you feel walking alone in this area after dark? (1 Very safe - 4 Very Unsafe)
GNDR Gender (1 Male, 2 Female)

Here's the sample implied covariance matrix

We can see that there are noticeable correlations especially between the satisfaction indicators. This is something to keep in mind, as it might hinder our analysis later.

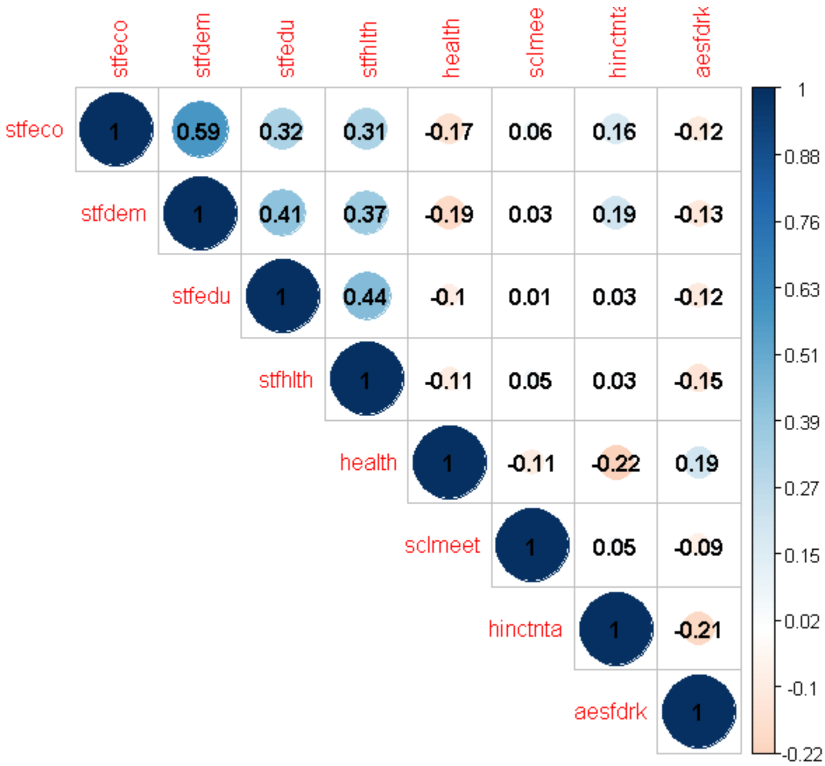

Figure 1: Sample implied Covariance Matrix

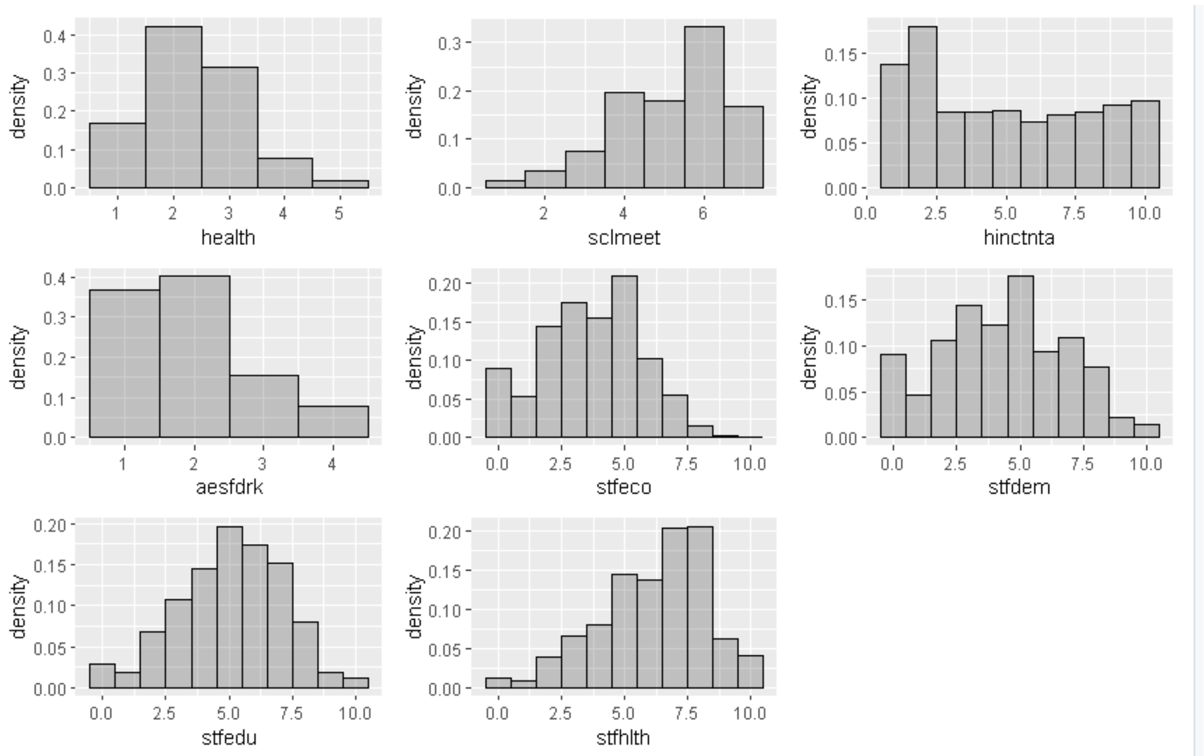

Figure 2: Distribution of our indicators

As we can see in Figure 2, we can affirm that some variables (aesfdrk, health, sclmeet, hinctnta, stfhlth) are non-normal. For this reason, we will use the Robust ML estimator

(Brown, T.A. (2006), Confirmatory Analysis for Applied Research. Guilford: New York, Chapter 9, pages 363-411). We can also notice that the distribution of stfhlth is left-skewed; it's not a surprise as French healthcare system is one of the best in the world (https://internationalliving.com/countries/france/health/).

Here's a look at some descriptive statistics of our data:

Variables	Mean	SD
stfeco	3.68	2.01
stfdem	4.33	2.48
stfedu	5.08	2.07
stfhlth	6.19	2.13
health	2.36	0.9
sclmeet	5.17	1.41
hinctnta	4.99	3.05
aesfdrk	1.94	0.91

Table 1: Descriptive statistics of our data

Modeling Strategy

First, We will use a simple CFA model with 2 latent variables (QOL and trust in government), with each of them measured by 4 indicators described in the section "Research Questions", and we will examine the fit of our measurement model. Our structural model posits that having a better quality of life is more likely to result in a greater confidence in government. We'll try to see in what extent it is true. Then, we'll do a multigroup analysis to test check whether our parameter estimates vary between male and female.

Analysis and Results

Measurement Model

We want to check if our measurement model is well specified (i.e., good-fitting, strong and interpretable factor loadings and factor correlations). We have (8*9)/2=36 pieces of information, 6 factor loading freely estimated (because 2 are fixed by default), 8 measurements errors, 2 latent variable variances and 1 latent variables covariance. The degree of freedom is equal to 36-17=19, hence the model is over-identified. Note that since "health" is fixed to 1 by default, our latent variable "qol" goes to the same direction as "health" (1 Very good - 5 Very bad), i.e when "qol" goes down, it means that quality of life is better.

Let's now fit our CFA model. In order to measure goodness of fit, we'll use the Standardized Root Mean Square Residual, the Root Mean Squared Error of Approximation, the Comparative Fit Index and the Tucker-Lewis Index. Here's a list of the fit indices that we got from this model:

Fit measures	Value
SRMR	0.041
Robust RMSEA	0.71
CFI	0.911
TLI	0.868

Table 2: Fit measures

Cutoff indices that we are going to use are : SRMR acceptable if <0.08, RMSEA acceptable if <0.05, CFI acceptable if >0.95, TLI acceptable if >0.95 (Brown, T.A. (2006). Confirmatory Analysis for Applied Research. Guilford: New York). None of our fit indices are considered satisfactory, so we want to see where are localized areas of ill fit, by looking at modification indices.

	Modification indices
stfedu∼stfhlth	140.319
stfeco∼stfdem	72.415
stfdem∼stfhlth	27.276
stfeco∼stfedu	25.855
stfeco∼stfhltl	14.245

Table 3: Modification indices

We notice that modification indices are really high for some of he covariances between indicators (stfedu with stfhlth and stfeco with stfdem, 140.319 and 72.415 respectively). In order to relax those parameters, we need to have strong theory and explanations that can support our decision to free those parameters. French healthcare system is unarguably one of the best in the world, with French government generally refunding patients 70 percent of most healthcare costs. Generally, the more educated a person is, the more satisfied that person is about the education system, and being educated also implies that he's aware of how good the French healthcare system is. It makes sense to have a covariance parameter between those two items.

However, even if it is tempting to freely estimate the covariance between stfeco and stfdem in order to improve the fit of our measurement model, we didn't find any theory that could possibly explain such a decision. This is why we won't freely estimate that parameter. Now let's check again the fit of our newly specified measurement model:

Fit measures	Value
SRMR	0.023
Robust RMSEA	0.03
CFI	0.985
TLI	0.977

Table 4: Fit measures

All our fit indices are good if we take the same cutoff indices as earlier.

Structural Part of the Model

We want to focus on our structural model, i.e causal relations among our latent variables. We want to check how quality of life affects confidence in government.

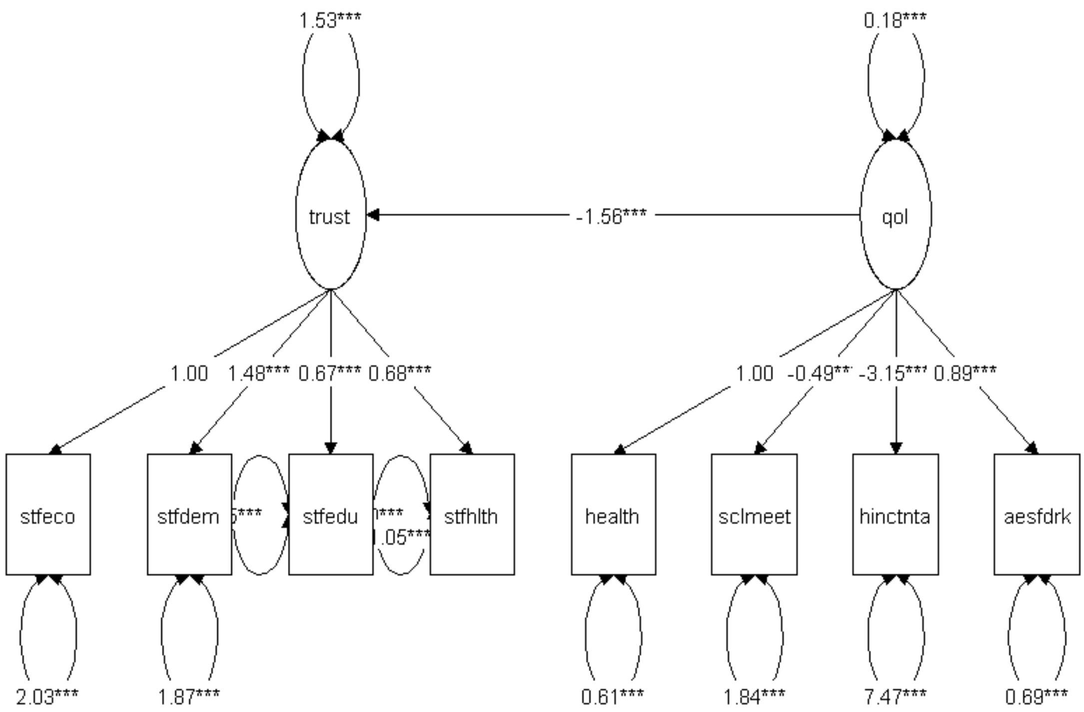

Figure 3: Plot of SEM (estimate of covariance between stfedu and stfhlth not showing)

Fit indices are the same as in our measurement model, all indicating a good fit. Now let's take at our parameter estimates.

Factor loadings	Estimates	Std.all
qol=~health	1	0.478
qol=~sclmeet	-0.491	-0.152
qol=~hinctnta	-3.146	-0.439
qol=aesfdrk	0.888	0.412
trust=~stfeco	1	0.701
trust=~stfdem	1.483	0.835
trust=~stfedu	0.665	0.454
trust=~stfhlth	0.680	0.449

Table 5: Factor loadings

Unsurprisingly, we can see that the satisfaction indicators are all positively associated with trust. Standardized parameteres are all above 0.4, indicating that trust is well measured by the satisfaction indicators (Brown, T.A. (2006). Confirmatory Analysis for Applied Research. Guilford: New York, page 130). Quality of life is also well measured by his indicators except 'sclmeet', where the standardized estimate is -0.152, showing that quality of life doesn't really explains much of the variance of that indicator. We made the hypothesis that a richer social life leads to a better quality of life, and we still think it is generally the case. The problem here is that meeting socially a lot of people doesn't necessarily indicates a good social life, as it also depends on how well does one connect with those people, and how much does one enjoy spending time meeting with those people. This is why 'sclmeet' might not be the best indicator to measure the quality of social life, and hence doesn't measure well our latent variable quality of life. However, we can affirm that good health, high income and feeling of safety are generally related to a good quality of life.

Regression	Estimates	Std.all
trust~qol	-1.555	-0.471

Table 6: Effect of QOL on Trust

An 1 unit increase in 'trust' corresponds to a -1.55 unit decrease in 'qol', which is logical since a smaller 'qol' indicates a better quality of life, like we mentioned at the beginning of our analysis. The standardized parameter estimate is equal -0.471, meaning that quality of life accounts for 0.471^2=22 percent of the variance of our latent variable 'trust'. From this output, we can say that quality of life definitely does have significant impact on trust in government in France, which is in line with the hypothesis we made, that French people really value their quality of life, to the point that it does affect their confidence towards the overall efficiency of the government. Since 78 percent of the variance in 'trust' is still left unexplained, there are definitely some improvement to be made in our model in order to better explain trust in French government. However, it is a good basis for future research.

Multigroup SEM

Now, let's do a multigroup CFA between male and female. We want to check potential aspects of invariance across genders. Our analysis will be split into three steps, corresponding to the three conditions of configural, metric and scalar invariance. Configural invariance is when there is the same factor structure across groups, but parameters are estimated freely. Metric invariance is when factor loading are equivalent across groups. Scalar invariance is when factor loading and item intercepts are equivalent across groups.

To examine configural invariance, the same model is examined separately for each group by using SEM. We will evaluate the fit of the model using a common criteria recommended by the literature: CFI, TLI, SRMR and RMSEA (Hu, L.-t., and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling).

Fit measures	CFI	TLI	SRMR	RMSEA
Values	0.99	0.985	0.022	0.022

Table 7: Fit indices for Configural invariance model

From the fit indices, we can establish configural invariance; the same model fits the data well across groups. The second step in our invariance examination is to test whether there is metric invariance or not.

Model	Df	Chisq	Pr(>Chisq)
fit_configural	36	56.059	
fit_metric	42	63.457	0.3706
fit_scalar	48	144.081	<2e-16

Table 8: Scaled Chi-Squared Difference Test (method = "satorra.bentler.2001")

Let's compare the baseline model with the metric invariance model. Differences between the two models are examined with the chi-square difference test. Pr(>chisq)=0.3706, the result of the chi-square difference test is non-significant, meaning that the metric invariance model is better than the baseline model because it fits the data equivalently to the baseline model but with better parsimony (higher degree of freedom). Metric invariance is then established between male and female french population, meaning that in our model, each item contributes to the latent construct to a similar degree in both groups. Satisfaction indicators measure trust in government the same way between male and female, and indicators measuring quality of life are equivalent between male and female.

However, a significant result (<2e-16) of the chi-square difference test between the metric invariance model and the scalar invariance model, shows that the metric invariance model is a better representation of our data, suggesting that item intercepts vary groups.

Conclusion

The purpose of this study was to develop a reliable scale to mesure trust in French government. Based on previous theory and analysis, we selected four satisfaction indicators, each measuring a certain aspect of our main latent variable. On the other hand, we introduced quality of life as a second latent factor, measured by general health, income, feeling of safety and social life. The analyses showed that our measurement model was overall psychometrically valid.

After analysing modification indices and freeing covariance parameter between satisfaction in education system and satisfaction between health system, we proceed on the structural part of the model. We found that quality of life had a significant influence on how French people trusted their government, which is in line with our former hypothesis. However, it has been shown that there is still a non-negligible variance of trust, that can't be explained by the overall quality of life.

In addition, our indicators measures trust in government and quality of life in a consistent way over male population and female population, because our analysis showed that we have the same factor structure over the two sub-samples with different types of respondents (male and female). Plus, metric invariance has been established during our analysis, showing that overall, our items contributed to trust and quality of life to a similar degree across genders.

However, to really establish the validity of our analyses, we need to extend with other dimensions of trust. In our study, we only focused on satisfaction items to measure trust, but we could improve our model by considering other items that might measure trust more accurately (OECD (2017), OECD Guidelines on Measuring Trust, OECD

Publishing, Paris). We could also improve the structural part of our model, in order to better understand variation in trust of the government.

However, our analyses, even if they are simple and not too complex, might help to further trust research in the French public administration field, by being the base of another study that would consider different dimensions of trust in government.

References

-Cooper, Christopher A., et al. "The Importance of Trust in Government for Public Administration: The Case of Zoning. 2008

-Benamouzig, Daniel. « Mesures de qualité de vie en santé. Un processus social de subjectivation? », Les Cahiers du Centre Georges Canguilhem, 2010

-Les Français et les enjeux de sécurité", Ifop pour Synopia, 2017

-Brown, T.A. (2006), Confirmatory Analysis for Applied Research. Guilford: New York

-https://internationalliving.com/countries/france/health/

-Hu, L.-t., and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling

-Muthén, L. K., Muthén, B. O. (2012). Chi-square difference testing using the Satorra-Bentler Scaled Chi-Square

-OECD (2017), OECD Guidelines on Measuring Trust, OECD Publishing, Paris

R Code

```
### DATA MANIPULATION ###
library("haven")
library("dplyr")
library("psych")
library('stringr')

### MODELING ###
library("lavaan")
```

```
### VISUALIZATION ###
library("corrplot")
library("tidySEM")
library("ggplot2")
library("patchwork")
library("MVN")

data <- read_sav("C:/Users/antoi/OneDrive/Bureau/ESS1-9e01_1.sav")
View(data)
data$gndr=as.double(data$gndr)

#Plot distribution of variables
h_health <- ggplot(data, aes(health)) +
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)

h_sclmeet <- ggplot(data, aes(sclmeet)) +
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)

h_hinctnta <- ggplot(data, aes(hinctnta)) +
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)

h_aesfdrk <- ggplot(data, aes(aesfdrk)) +
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)

h_stfeco<- ggplot(data, aes(stfeco)) +
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)

h_stfdem <- ggplot(data, aes(stfdem)) +
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)

h_stfedu <- ggplot(data, aes(stfedu)) +
```

```
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)

h_stfhlth <- ggplot(data, aes(stfhlth)) +
  geom_blank() +
  geom_histogram(aes(y = ..density..), binwidth = 1, colour = "black",
      alpha=0.3)



h_health+h_sclmeet+h_hinctnta+h_aesfdrk+h_stfeco+h_stfdem+h_stfedu+h_stfhlth

#sample implied covariance matrix
data_selected<- data %>% select(stfeco,stfdem,stfedu,stfhlth, health,
    sclmeet, hinctnta, aesfdrk)
obscov<-cov(data_selected, use = "pairwise.complete.obs")
obscov<- cov2cor(obscov)

corrplot::corrplot(obscov,
                  is.corr = FALSE,      # whether is a correlation matrix
                  method = "circle",    # magnitude of covariance as circles
                  type = "upper",       # remove the bottom of the covariance
                      matrix
                  addCoef.col = "black" # add to the plot the coefficients
)

#descriptive stats
descriptive_ess <- as.data.frame(psych::describe(data_selected))

descriptive_ess <- dplyr::select(descriptive_ess,
                                 n,
                                 mean,
                                 sd,
                                 median,
                                 min,
                                 max,
                                 skew,
                                 kurtosis)

descriptive_ess

#measurement model
```

```
measurement_model<-'##Quality of life##
qol=~ health + sclmeet + hinctnta + aesfdrk
trust=~stfeco+stfdem+stfedu+stfhlth
'

fit_model <-cfa(measurement_model, data=data, estimator="MLR")
summary(fit_model, standardized=T, fit.measures=T)

modindices(fit_model, sort = TRUE, maximum.number = 10)

#measurement model modified
measurement_model2<-'##Quality of life##
qol=~ health + sclmeet + hinctnta + aesfdrk
trust=~stfeco+stfdem+stfedu+stfhlth
stfedu~~stfhlth
'

fit_model2 <-cfa(measurement_model2, data=data, estimator="MLR")
summary(fit_model2, standardized=T, fit.measures=T)

#sem
sem_model<-'qol=~ health+ sclmeet + hinctnta + aesfdrk
trust=~stfeco+stfdem+stfedu+stfhlth
stfedu~~stfhlth
trust~qol'
fit_sem<-sem(sem_model, data=data, estimator="MLR")
summary(fit_sem, standardized=T, fit.measures=T)

#plotting SEM
lay<-get_layout("", "","trust","","","","qol","",
               "stfeco","stfdem","stfedu","stfhlth","health","sclmeet","hinctnta","aesfdrk",
                  rows=2)
plot_sem<-graph_sem(model=fit_sem, layout=lay, angle=170)
plot_sem

#configural invariance
fit_confsem<- sem(model=sem_model, data=data, estimator="MLR", group="gndr")
summary(fit_confsem, standardized=T, fit.measures=T)

#metric invariance
fit_metricsem<- sem(model=sem_model, data=data, estimator="MLR",
   group="gndr", group.equal = c("loadings"))
summary(fit_metricsem, standardized=T, fit.measures=T)
```

```
#scalar invariance
fit_scalarsem<- sem(model=sem_model, data=data, estimator="MLR",
    group="gndr", group.equal = c("loadings","intercepts"))
summary(fit_scalarsem, standardized=T, fit.measures=T)

#chi-square difference test
table_anova <- list(anova(fit_confsem, fit_metricsem),
                  anova(fit_metricsem, fit_scalarsem)) %>%
  reduce(rbind) %>%
  .[-c(3),]

table_anova
```