Structural Equations Assignment (B-KUL-G0B65A)

Exploring the Complex Interrelations Among Political Efficacy, Trust and Satisfaction with the State of Affairs in Hungary in 2015

A Structural Equation Modeling Approach Using Data from the European Social Survey Round 7

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A paper presented to

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May 18, 2023

Contents

Problem Statement and Hypotheses

1.1 Broader context and relevance

The complex interplay among political efficacy, trust and satisfaction with the current state of affairs are crucial factors influencing public sentiment and political engagement [3] and are thus presumably indicators of the broader health of democratic societies [14].

Political efficacy refers to individuals' beliefs in their ability to participate effectively and influence political processes. It is an important precursor of political participation, a highly desirable trait in democratic societies [25].

Interpersonal trust refers to the degree to which individuals feel comfortable relying on others and expecting positive outcomes from their interactions [24]. Interpersonal trust presupposes reciprocity, which is quintessential theoretically for the satisfactory functioning of democracies. Furthermore, research suggests that interpersonal trust is positively correlated with political participation, in particular with joining political organizations and taking on more active roles in politics in general [22].
In the current paper, institutional or political trust is measured by respondents reported levels of trust in the legal system, the police, politicians, political parties, the European and the Hungarian parliaments and the United Nations. In the literature, institutional trust is often deemed desirable for citizens' acceptance of government authority and its legitimacy, thus fostering the effective functioning of democracies. [11].

Trust, which encompasses both interpersonal and institutional trust plays a pivotal role in citizens' perceptions of the reliability, credibility, and fairness of the systems in place [20]. Furthermore, both interpersonal and institutional trust promote compliance with the rule of law and public order [15].

Satisfaction with the current state of affairs, on the other hand, reflects individuals' overall contentment with various aspects of the sociopolitical landscape, including the economy, government performance, the functioning of democracy, education, healthcare and more.

Rosanvallon and Hoogte et al., argued independently of each other, that in contemporary democratic societies the assertive citizen who highly values democracy yet has a certain level of distrust towards authority and questions or criticises the status quo is an important hallmark of its well-functioning nature [23][13].

Drawing on these studies, the current paper aims to explore the complex relationship and interplay among political efficacy, trust, satisfaction with the state of affairs and certain select sociodemographic factors in the Hungarian context, which despite its unique sociopolitical landscape and the significance of the topic, seem to have garnered less academic attention so far.

1.2 Research Questions

1. How does trust impact political efficacy in Hungary?
2. What is the relationship between satisfaction with the state of affairs and political efficacy

in Hungary?

3. How do these relationships differ among different demographic groups?
4. Do the items selected measure political efficacy equivalently across genders?

1.3 Hypotheses

H1: Higher levels of trust are positively associated with political efficacy [22].
H2: Higher levels of satisfaction with the state of affairs are positively associated with political efficacy [3].
H3: Trust and Satisfaction with the state of affairs serve as mediators in the relationship between political efficacy and certain sociodemographic groups [3] [6].
H4: Items are expected to measure political efficacy equivalently across genders, at least at the metric level.

Description of the Data Set Used

2.1 The European Social Survey Round 7

The data was obtained from round 7 of the European Social Survey (ESS), a biennial cross-national survey on attitudes, behaviour and a wide range of social and political topics. Round 7 in Hungary was conducted in 2015 using multistage stratified random sampling [27].

The target population included "All persons aged 15 and over resident within private households, regardless of their nationality, citizenship, language or legal status" [7]. The Sampling Frame was the Settlements and the National Population Registry from the Central Office for Administrative and Electronic Public Services (KEH KH) [26].

The research relied on a 2-domain sampling design. The first domain contained the capital and the following 23 largest settlements. The second domain contained the rest of the country not included in the first domain. In the first domain, a single-stage design was applied, where all 23 districts of Budapest and the 23 other largest settlements each constituted a single stratum. Respondents were then picked from each stratum using simple random sampling. In the second domain, a 2-stage design was applied. First, the settlements were stratified based on 7 geographical regions and settlement type (city or village), i.e., number of inhabitants. Respondents within the strata were selected using probability sampling, with the probabilities being proportional to the size of the target population within settlements [26].

Data was collected face-to-face via computer- and/or mobile-assisted interviews [26].

A subset of variables relevant to the research questions and hypotheses were selected as presented in table A.1. The Hungarian case contained 1698 observations.

2.2 Data processing and cleaning

The data underwent preprocessing before publication. Wild codes, invalid, out-of-range, extreme and certain missing values were addressed without compromising data quality or reliability [16][9].

To err on the side of caution, as part of the current assignment, the data was filtered for careless respondents using the Mahalanobis criterion which calculates how much a data point deviates from the multivariate mean. It essentially flags respondents whose combination of responses are highly unusual compared to other participants. In the current data set no respondents were flagged as potentially careless, therefore no filtering was needed.

However, the data still contained a proportionately significant amount of missing values, unsurprisingly, given the sensitive nature of the topic.

2.3 Descriptive statistics

There was only one out-of-range value detected in 'edlvdhu' (= highest level of education attained) which in the original questionnaire was meant to distinguish NAs from 'Other'. In order to keep the simple ordinal nature of the variable, this data point was replaced with an 'NA'. Other than that, all variables were within their expected range. Indicator variables were measured on 11-point Likert scales. Miscellaneous and sociodemographic variables ranged from binary to 14-point ordinal variables.

Respondents were between the ages of 15 to 92 with an average age of around 50. Indicators associated with political efficacy ('actrolg', 'cptppol', 'psppipl', 'psppsgv', 'ptcpplt') were all at the lower end of the spectrum, around 2 out of 10, implying relatively low levels of political efficacy. Variables relating to satisfaction with the current state of affairs ('stfeco', 'stfgov', 'stfgov', 'stfdem', 'stfedu', 'stfhlth') varied but were in general around 4 out of 10, indicating a moderate level of satisfaction. Likewise, items relating to interpersonal trust seemed to have moderate levels of around 4 to 5 out of 10. Items relating to institutional trust painted a more nuanced picture, with trust in the national political apparatus ('trstplt', 'trstprt', 'trstprl') being at the lower end of the scale, the European Parliament ('trstep') gaining moderate, while the police ('trstplc') and the UN ('trstun') garnering slightly higher levels of trust apparently.

Most items showed moderate to low standard deviations, with means and medians mostly being close to each other. Skewness and kurtosis remained below absolute value 1, except for gender, being a binary variable with possible values 1 and 2, and income, education and age, all having a negative kurtosis slightly below -1. Most variables had negative kurtosis, indicating lack of "heavy tails", i.e., opinions on most items did not seem too polarized.

2.4 Data limitations

The ESS provides extremely high quality data but like all researches, it has some limitations. However, the response rate was 52.7% [26], if non-response is systematic, it might still be a cause for concern. For example, face-to-face interviews might introduce social desirability bias, particularly given the sensitive nature of the topic.
Furthermore, the interviews were conducted in the official language, but as mentioned previously the target population included individuals of all nationalities residing in Hungary from aged 15 and over. Getting lost in translation, not conveying the message to each other accurately might be another source of bias.

Modeling Strategy

3.1 Model assumptions

CFA and SEM analysis relies on 4 key assumptions: a linear relationship between indicators and latent variables, sufficient sample size and multivariate normality of indicators [4, p. 21].

Generally, sample sizes greater than 200 are considered sufficient for confirmatory factor analysis. The current sample contained 1698 observations, substantially exceeding this threshold.

Given that the data came from a cross-sectional survey that relied on probability sampling, it is reasonable to assume independence of observations.

To assess linearity, observed indicators were plotted against latent factor scores and in case of Trust as a second order latent variable, its factor scores were plotted against that of its indicator factors', as presented in figures A.39 to A.48. Though varying in strength of association, patterns appeared mostly linear, however homoscedasticity assumptions were violated here and there.

Univariate normality was assessed as "although univariate normality does not ensure multivariate normality, univariate non-normality does ensure multivariate non-normality" [4, p. 380]. The Shapiro-Wilk test was applied instead of the Kolmogorov-Smirnov test, as the former is apparently more robust to 'ties' (equal-valued observations). The Kolmogorov-Smirnov test assumes continuous data. Given the W statistics and low p-values for all variables, the null hypotheses of univariate normal distributions were rejected, and hence concluded that the data cannot be multivariate normally distributed either. Subsequent Henze-Zirkler's tests confirmed this as well.

3.2 Handling missing data

After inspection of missing data patterns, as per figure A.38, Little's (1988) [17] χ^2 test statistic was used to assess whether data was missing completely at random or else. Given the high statistic and low p-value, it was concluded that the data was not missing completely at random (not MCAR).

Although, careless respondents were not detected using the Mahalanobis criterion, to err on the side of caution, people who had more than 50% of their responses missing from the scale were filtered out, this resulted in a loss of 7 respondents, leaving us with a final sample size of 1691.

There was still a proportionately significant amount of missing data left in the data frame and it was not possible to assess whether these were missing at random (MAR) or missing not at random (MNAR) but given the sensitive nature of the topic and the missing data pattern, they were more likely the latter. Nonetheless, the analysis was continued.

Working with the assumption that the data were in fact missing at random (MAR), full information maximum likelihood estimation was employed to handle missingness.

3.3 Operationalization

The data was analysed using structural equation modelling due to its ability to handle latent factors and the complex nature of multivariate data while taking measurement errors into account. The Multiple Indicators Multiple Causes (MIMIC) model allowed for fitting formative and reflective indicators in the same model, thus, making it possible to explore the influence of certain sociodemographic variables on the latent factors. Mediation Analysis was used to test the hypothesis relating to certain factors' mediating effects on Political Efficacy, while multi-group analysis was applied to check measurement invariance across gender groups.

The indicator variables were ordinal, measured on 11-point Likert scales. The underlying concepts could be thought of as continuous variables due to their spectrum-like nature. One alternative could have been to model out non-normality using mean and variance adjusted weighted least squares estimator (WLSMV) but that would have required a complete data set, without missing observations. First, missing data would have had to be imputed and then WLSMV could have been applied. In fact, this approach was considered for some of the models initially (see R code in Appendix), but results did not differ significantly to using maximum or robust maximum likelihood estimators. This was in line with existing literature and simulation studies that have shown that if sample size is large, the data is not too heavily skewed and the scales are measured on 5 points or more, maximum likelihood estimation in confirmatory factor analysis remains fairly robust, i.e., non-normality can be ignored [10][1][28]. If these conditions are not met though, standard errors would be biased like in regression, and the χ^2 test becomes very sensitive to deviations from normality [18]. Given that in the current data set, all these conditions were met, using regular maximum likelihood estimation (ML) seemed most appropriate. Robust maximum-likelihood (MLR/MLM) was also considered and tried but again results did not differ significantly and given that using MLR would have required scaling χ^2 values back before ANOVA could have been applied and given that according to literature using ML or MLM does not affect parameter estimates only standard errors, which in this case was not an issue due to having met the aforementioned conditions, regular maximum likelihood estimation was deemed most appropriate and was hence used in the current analysis.

The equation of the maximum likelihood estimation in the context of SEM is as follows,

$$F_{\mathrm{ML}} = \ln|\mathbf{S}| - \ln|\mathbf{\Sigma}(\boldsymbol{\theta})| - \mathrm{tr}(\mathbf{S}\mathbf{\Sigma}^{-1}(\boldsymbol{\theta})) - p \tag{3.1}$$

where $\ln|S|$ stands for the natural logarithm of the determinant of the sample variance-covariance matrix, $\ln|\Sigma(\theta)|$ is the natural logarithm of the model implied variance-covariance matrix Σ as a function of the true data generating mechanism θ and p stands for the number of parameters in the model.

3.4 Model fit evaluation criteria

In the strictly confirmatory approach the global fit of a single model is evaluated based on the χ^2 statistic $F_{ML}(N-1)$. If the χ^2 value is statistically significant, the model is rejected. If there are k observed variables in a linear model with t unconstrained parameters to be estimated, then the number of degrees of freedom can be calculated as

$$df = \frac{k(k+1)}{2} - t \tag{3.2}$$

Another commonly used rule of thumbs is to reject the model if the χ^2 test value divided by the degrees of freedom exceeds 3 [4] [18]. However, the χ^2 test is sensitive to sample size and deviations from normality. Furthermore, sparse models rarely fit reality 100%. Therefore in the current paper alternative and model generating approaches were employed as well.

As per the alternative models approach alternative global fit indices were considered for each model while nested models were assessed using χ^2 different tests which compared the more restricted model to the more lenient one, the null hypothesis being that the former fits the data just as well as the latter.

Alternative global fit indices used were as follows:

- Root Mean Square Residual (RMR) - Rule of thumb: $<.08$ indicates acceptable fit
- Root Mean Squared Error of Approximation (RMSEA) - Rule of thumb: $<.05$ indicates acceptable fit
- Comparative Fit Index (CFI) - Rule of thumb: $>.90$ indicates acceptable fit
- Tucker-Lewis Index (TLI) - Rule of thumb: $>.90$ indicates acceptable fit

As per the model generating approach, local misfit (modification) indices were taken into account as well.

3.5 Models fitted

Before fitting the models, the observed correlation matrix of the indicators was examined. As per figure A.49, in line with the paper's prior theoretical assumptions, 4 distinct clusters could be observed. It appeared that country-level items of Institutional Trust also moderately correlated with items relating to Satisfaction with the Current State of Affairs, which makes sense and can be substantiated, given that current state of affairs in any given country is highly dependant on government institutions.

Next, to test our assumptions more formally congeneric single-factor latent variables were fitted for Political Efficacy (PolEf), Institutional (or Political) Trust (INSTT), Interpersonal Trust (IP), and Satisfaction with the current State of Affairs (SatCSA).

To ensure model identification, the latent factors were scaled by constraining the factor loadings of the marker items to one. Initially, in each model, the statistical assumption was made that error variances among indicators were uncorrelated and as per equation 3.2, it was ensured that the number of freely estimated parameters t did not exceed the number of pieces of information available $\frac{k(k+1)}{2}$, i.e., that the degrees of freedom was positive or at least zero.

3.5.1 Political Efficacy

For latent variable Political Efficacy a CFA model with five observed variables was fit. The variables being 'actrolg', 'cptppol', 'psppipl', 'psppsgv', and 'ptcpplt'. Initially, global model fits remained below threshold, with a significant χ^2 value of 631.64, CFI of 0.87 and TLI of 0.74. Following the alternative modelling approach, using modification indices, certain constrains were sequentially relaxed. Modification indices suggested that allowing variables 'Able to take active role in political group' (actrolg) and 'Confident in own ability to participate in politics' (cptppol) to correlate would improve model fit by a 523.73 reduction in the χ^2 statistic and with an expected fully standardized parameter change of 0.617. This change is theoretically justified. These variables relate to internal efficacy, the belief that one can understand and therefore has the capability to participate in politics, whereas the other three variables relate to external efficacy, the belief that decision makers, the government etc. will respond to one's needs [2]. After this modification, the fit has improved substantially. The χ^2 value was still significant but the test statistic went down to 55.72, CFI up to 0.99 and TLI to 0.97. Nonetheless, RMSEA, with 0.087, was still above the desired level of 0.05. Lastly external efficacy-related variables 'psppsgv' and 'ptcpplt' were allowed to correlate which resulted in a near-perfect fit. χ^2 remained significant but barely, and given the massive sample size this is acceptable. CFI reached 1.0, TLI 0.99 and RMSEA 0.05, as per table A.3. The χ^2 different tests among subsequent models confirmed that indeed, incremental changes led to better and better model fits and that it was not due to chance, see table A.4.

3.5.2 Satisfaction with the Current State of Affairs

For the latent variable Satisfaction with the Current State of Affairs 5 indicators were fitted resulting in a significant χ^2 value of 207.68, a CFI of 0.96, a TLI of 0.92 and an RMSEA of 0.15, indicating that the fit could be improved. Modification indices suggested allowing for error correlations between 'Satisfaction with the State of Education' (stfedu) and Satisfaction with the State of Healthcare (stfhlth). This theoretically makes sense, as education and healthcare are interdependent. Good education often leads to better health outcomes, while good health enables one to fully participate in education. Both are highly dependent on government funding, which is even more true in the Hungarian context, given that both education (including obtaining one's first higher-education degree) and healthcare (including dentistry) are generally free [12]. This amendment resulted in significant model improvement. The p-value was still significant, but CFI reached 1.0, TLI 0.99 and RMSEA 0.05. Modification indices suggested that relaxing the constraint on no error correlations between 'stfeco' and 'stfgove' would further improve model fit. Indeed, after this modification, the χ^2 p-value was no longer significant, CFI and TLI reached 1.00 and RMSEA went down to 0.02. Allowing these two items to correlate can be justified by the fact that people often judge governments' performance and competence in relation to their perception of how well the economy is doing. Hence, satisfaction with the economy and satisfaction with the government can correlate for reasons other than political efficacy as well, such as perceived performance. Following the alternative models approach model fits were compared using χ^2 difference tests, see table A.6, that confirmed that each sequential step resulted in a better fit not due to chance.

3.5.3 Institutional Trust

The latent variable Institutional Trust was fitted using 7 indicator variables. The initial fit was suboptimal with a χ^2 value of 1947.16 to 14 degrees of freedom, a CFI of 0.76, a TLI of 0.65 and an RMSEA of 0.29. Modification indices suggested that error correlations should be allowed between 'trstplt' and 'trstprt', which resulted in an 831.538 improvement in the χ^2 statistic and an associated fully standardized parameter change of 1.437. Again, this made theoretical sense, given that parties are made up of politicians, these two questions might be measuring something that overlaps substantially. This resulted in fit improvement. The χ^2 statistic remained significant, CFI went up to 0.84, TLI to 0.75 and there had been a slight decrease in RMSEA to 0.24. Next, as suggested by the modification indices, the 'trstep' and 'trstun' was allowed to covary. Again, this can be theoretically justified, given that these two variables relate to international political actors, while the other five relate more to the national level. This change resulted in further improvements. χ^2 was still significant but went down by 810.110 accompanied with an expected fully standardized parameter change of 0.789. CFI and TLI reached their desired thresholds, with 0.97 and 0.94 respectively. Nonetheless, RMSEA remained high at 0.11. And finally, 'trstlgl' and 'trstplc' were allowed to covary. This resulted in an improvement of 140.356 in the χ^2 statistic accompanied with an expected fully standardized parameter change of 0.417. CFI and TLI reached 0.98 and 0.97 respectively, while RMSEA lowered to 0.08 hence remaining above the desired level of 0.05. This change can be justified by the fact that the police is the primary enforcer of the rule of law and public order. Modification indices indicated no substantial further improvement any more. All expected parameter changes remained below 0.2, see tables A.7 and A.8.

3.5.4 Interpersonal Trust

The latent variable Interpersonal Trust was fitted using 3 indicator variables, resulting in a just-identified model fit (df=0), with a single unique solution. Therefore, the aforementioned model fit indices were not applicable.

3.5.5 Proposed measurement model

Combining these single-factor models into a 5-latent factor simultaneous CFA model provided the final complete measurement model, with Trust being a secondary latent variable to Institutional (Political) and Interpersonal Trust, correlating with Satisfaction with the Current State of Affairs and Political Efficacy, as presented in figure A.52.

The defining model equations were as follows:
Trust $= \theta_1 \cdot \text{INSTT} + \theta_2 \cdot \text{IP} + \epsilon_1$,

SatCSA = $\theta_3 \cdot$ stfeco + $\theta_4 \cdot$ stfgov + $\theta_5 \cdot$ stfdem + $\theta_6 \cdot$ stfedu + $\theta_7 \cdot$ stfhlth + ϵ_2,
PolEf = $\theta_8 \cdot$ actrolg + $\theta_9 \cdot$ cptppol + $\theta_{10} \cdot$ psppipl + $\theta_{11} \cdot$ psppsgv + $\theta_{12} \cdot$ ptcpplt + ϵ_3,
INSTT = $\theta_{13} \cdot$trstlgl+$\theta_{14} \cdot$trstplc+$\theta_{15} \cdot$trstplt+$\theta_{16} \cdot$trstep+$\theta_{17} \cdot$trstun+$\theta_{18} \cdot$trstprt+$\theta_{19} \cdot$trstprl+ϵ_4,
IP = $\theta_{20} \cdot$ ppltrst + $\theta_{21} \cdot$ pplfair + $\theta_{22} \cdot$ pplhlp + ϵ_5.
Furthermore the following error terms were allowed to covary: trstplt ∼∼ trstprt, trstep ∼∼ trstun, trstlgl ∼∼ trstplc, stfedu ∼∼ stfhlth, and actrolg ∼∼ cptppol.

The model had 160 degrees of freedom and a χ^2 test value of 901.4, as per figure A.1, indicating that the model implied covariance matrix was significantly different from the observed one, but as previously mentioned, the χ^2 test statistic is sensitive to sample size and deviations from normality, and thus, it is often rejected in such large samples. The Comparative Fit Index (CFI) was 0.966, the Tucker-Lewis Index (TLI) 0.96, both being in the desirable range, indicating good model fit. The RMSEA was 0.052 indicating a borderline reasonable to good fit, see figure A.2. SRMR was 0.044, again, indicating a good model fit, as per figure A.3. All indicators loading on their respective latent factors were positive, significant and salient (above 0.40), as per figures A.52 and A.3. Positive factor loadings are a result of all questions having the same direction. This, however, might introduce distortion due to the possible presence of acquiescence bias.

Figure A.3 shows both the standardized and the unstandardized factor loadings. The first non-standardized factor loading of each latent variable has been set to one for identification purposes. All factor loadings appear salient, no candidates for removal.

Figure A.4 shows the covariances among latent factors and among the indicators we allowed to covary. All p-values are significant. Looking at the fully standardized covariances, it appears that latent variables Trust, Satisfaction with the Current State of Affairs and Political Efficacy are all positively related, with the fully standardized covariates indicating moderate to strong positive associations among them.

Standardized variances were all positive and below one except for factor variances that had been set to 1 for identification purposes A.6, i.e., no Haywood-cases were present.

Results

4.1 Results

Testing the validity of the measurement model was followed by applying the theoretical assumptions made at the beginning of this paper to test the proposed hypotheses.

4.1.1 Multiple indicators, multiple causes model (MIMIC)

First, the hypothesis was posited that certain sociodemographic factors significantly impact the level of political efficacy among respondents. To test this assumption latent factors and indicators of the measurement model were regressed onto covariates that represented group membership. This approach is often referred to as CFA with covariates or MIMIC models [21].

First, a MIMIC model was specified to test for differences in latent construct, Political Efficacy (PolEf), based on political orientation (lrscale). The path diagram and the 'lavaan' output of this model is presented in figure A.53 and in figures A.7 to refA.12. The assumption was made that people whose political orientation aligned with the current political leadership, would feel more in control and more able to influence politics, thus would score higher on Political Efficacy, particularly on items relating to external efficacy. Furthermore, it was hypothesized, that items measuring external efficacy would function differently for people with different political orientations.

For the first MIMIC model, where Political Efficacy was regressed on political orientation, the algorithm converged in 102 iterations, only a couple more then for the measurement model. MIMIC models are generally not as computationally expensive as multi-group models, for example, as they estimate less parameters.

No significant direct effect of the covariate on the latent factor was observed, i.e., no evidence of population heterogeneity was found, factor means did not differ at different levels of the covariate. Global fit indices indicated an acceptable fit, TLI being 0.945, CFI 0.953 and RMSEA and SRMR being slightly above the recommended level with 0.060 and 0.074 respectively, indicating a borderline reasonable to good fit, see table A.12. Local fit indices did not suggest any changes that would have resulted in a salient and theoretically justifiable improvement. Looking at the 'lavaan' output in figure A.9 and in figure A.53, it can be observed that political orientation had a small, non-significant effect on Political Efficacy. It appears that the latent factor is not really structured along the gradients of political orientation, or at least not in a linear fashion.

Next the same MIMIC model was fit including direct effects on indicator items relating to external political efficacy, as per figures A.13 and A.54. Again, there seem to have been no significant effects, i.e., no evidence of measurement invariance was found. The model fit was reasonable to good. The hypothesis that political efficacy or its indicators would be affected by political orientation had to be rejected. Unlike multiple-groups CFA, MIMIC models can test only the invariance of indicator intercepts and factor means and they assume that all other measurements and structural parameters are the same across all levels of the groups [4].

In the subsequent models Political Efficacy was regressed on income (hinctnta) A.55, income and feeling close to one's country (fclcntr) A.56, income and age (agea) A.57, income, age and gender (gndr) A.58 and income age and education (edlvdhu) A.59, respectively.

Global fit indices have been summarized in table A.12. CFI and TLI reached their desired thresholds for all MIMIC models specified, with 0.95 and 0.94, respectively, indicating a good fit. Nonetheless, RMSEA remained slightly above its ideal level with a value of 0.06. Overall, all model fits were borderline reasonable to good, only differing slightly in χ^2 statistics and degrees of freedom. Otherwise, model fits seemed identical.

As per figure A.16, income had a significant but small effect on Political Efficacy. One standard deviation increase in income, was associated with 0.097 standard deviation increase in Political Efficacy. However, small effect sizes need to be interpreted with caution, especially, given the large sample size. As per figure A.21, feeling close to one's country had a barely significant and small effect on Political Efficacy when fit together with income.

Fitting income, age and highest level of education resulted in a small, non-significant income effect, and a small, significant, negative age and a somewhat more salient and positive education effect. Meaning that age was slightly negatively associated with Political Efficacy, but again the effect was very small. 1 unit increase in the scale (one step up) on highest level of education was associated with a 0.041 standard deviation increase in the latent factor, or 1 standard deviation increase in the former was associated with 0.116 standard deviation increase in the latter A.24.

Fitting all regressors in one MIMIC model yielded results presented in figures A.28 and A.60. Income (hinctnta) and feeling close to country (fclcntr) had small, non-significant effects but gender, highest level of education and age were significant, with age being the least salient.

Women scored 0.105 standard deviation lower then men on Political Efficacy. 1 standard deviation increase in age was associated with a 0.090 standard deviation decrease in the latent factor, equivalently, 1 year increase in age, was associated with 0.005 standard deviation decrease in the latent factor while 1 standard deviation increase in highest level of education was associated with 0.123 standard deviation increase in the underlying latent factor.

It appears that Political Efficacy (PolEf) was not really structured along the gradients of most sociodemographic factors considered here, or at least not in a linear fashion, except for maybe gender, highest level of education and possibly age.

4.1.2 Mediation

Next a mediation analysis was conducted to explore whether Trust and Satisfaction with the Current State of Affairs mediated the relationship among certain sociodemographic variables and Political Efficacy. The selected sociodemographic variables were age, highest level of education, income, gender, feeling close to one's country and political orientation.

Mediation analysis of Political Efficacy and Trust

First, the model for the mediation analysis between Trust and Political Efficacy was fit, see figures A.32 to A.35. The path diagram is presented in figure A.62. The CFI and the TLI were 0.95 and 0.94,respectively, indicating a relatively good fit.The RMSEA was 0.055, so just slightly above the recommended threshold. SRMR was 0.044, again, indicating a good fit, see table A.13. Therefore, taking a bit of error of approximation into account, this was considered a reasonable approximation, a reasonable fit to the data.

Political Efficacy (PolEf) was regressed on the sociodemographic variables selected (i.e., direct effects). Age (agea) had a statistically significant relationship with PolEf, but the regression coefficients were very small. Looking at the fully standardized coefficients, it can be observed that 1 standard deviation increase in age resulted in 0.095 standard deviation decrease in Political Efficacy. Alternatively, looking at the standardized coefficients based on latent variables, holding all else equal (partial regression), one year increase in age was associated with 0.005 standard deviation decrease in PolEf, see figure A.33.

The relationship between PolEf and highest level of education (edllvdhu) was also significant, but likewise negligible in effect size. One standard deviation increase in education was associated with 0.066 standard deviation increase in PolEf.

The relationship between PolEf and income (hinctnta) was also significant, but effects were small, negligible. Counterintuitively, one standard deviation increase in household income was associated with 0.077 standard deviation decrease in PolEf.

Being a woman was associated with 0.122 standard deviation lower PolEf scores. Feeling close to one's country was also significant, political orientation was non-significant but again, both had negligible effect sizes.

On the other hand, regressing Trust on the same variables (i.e., sociodemographic factors' direct effect on Trust), painted a more nuanced picture. All relationships were significant except for age and gender. Holding all else equal, one standard deviation increase in highest level of education was associated with 0.1, one standard deviation increase in income with 0.223 and being one standard deviation more to the right on the political spectrum with 0.349 standard deviation increase in Trust. Feeling close to one's country was reverse coded, therefore the results can be interpreted as follows: One standard deviation increase in 'fclcntr' (not feeling close to the country) resulted 0.248 standard deviation decrease in trust, i.e., the closer an individual felt to their country the higher they scored on Trust.

The direct effect of Trust on PolEf was strong and significant. One standard deviation increase in Trust was associated with 0.835 standard deviation increase in PolEf.

The indirect effects, i.e., the effect of select sociodemographic variables transmitted by the mediator variable, Trust, were insignificant for gender and age but were significant for education, income, feeling close to one's country and political orientation. The indirect effect of education on PolEf through Trust was positive and significant but rather small. The fully standardized regression coefficient was 0.084. The indirect effect of income, on the other hand was more salient, with 1 standard deviation increase in the indirect effect of income having been associated with 0.186 standard deviation increase in PolEf. Positive regression coefficients here indicate that the predictor has a positive relationship with Trust which in turn has a positive relationship with PolEf, conversely, negative coefficients indicate a negative relationship between the predictor and Trust which in turn transmits a negative effect to PolEf. The indirect effects of fclcntr and lrscale are also significant and their fully standardized effect sizes are more salient. Not feeling close to one's country (fclcntr is reverse coded) has a negative impact on Trust, which in turn results in a negative effect on PolEf. One standard deviation increase in the indirect effect of not feeling close to Hungary, resulted in 0.207 standard deviation decrease in PolEf, while one standard deviation increase in the indirect effect of political orientation (lrscale) resulted in 0.292 standard deviation increase in PolEf, indicating that being more to the right on the political spectrum had a positive effect on Trust which in turn mediated a positive effect to PolEf, see figure A.35.

Total effects are the sum of direct and indirect effects. Again, total effects of age and gender were insignificant, effect sizes were negligible, suggesting that age and gender did not significantly effect PolEf when considering both direct and indirect paths. On the other hand, total effects of education, income, feeling close to the country and political orientation had significant total effects.

The direct and indirect effects of Education through Trust were both significant and positive, the indirect effect accounting for more then half of the total effect (0.066 + 0.084 = 0.150). Education in total, directly and indirectly through Trust, seem to have significantly increased Political Efficacy.

The direct and indirect effects of Income through Trust were both significant. The former was negative, the latter positive. The indirect effect accounted for most of the total effect (-0.077 + 0.186 = 0.109). Income directly but mostly indirectly through Trust seem to have significantly increased Political Efficacy.

The direct and indirect effects of 'fclcntr' through Trust were both significant. The former was negative, the latter positive. The indirect effect accounted for most of the total effect (-0.077 + 0.186 = 0.109). 'fclcntr' directly but mostly indirectly through Trust seem to have significantly decreased Political Efficacy.

The indirect effects of Political Orientation through Trust was significant and positive. The direct effect was insignificant, negligible in size and negative. Therefore, the indirect effect accounted for most of the total effect (-0.061 + 0.292 = 0.230). Political orientation only indirectly, through Trust, seem to have significantly increased Political Efficacy.

Mediation analysis of Political Efficacy and Satisfaction with Current State of Affairs

Next, the model for the mediation analysis between Satisfaction with Current State of Affairs and Political Efficacy was fit, see figure see figures A.29 to A.31. The path diagram is presented in figure A.61. The CFI and the TLI were both close to or above 0.95, indicating a relatively good fit.The RMSEA was 0.063, so slightly above the recommended threshold. SRMR was 0.041, again, indicating a good fit A.13. Therefore, taking a bit of error of approximation into account, this was considered a reasonable approximation, a reasonable fit to the data.

Political Efficacy (PolEf) was regressed on the sociodemographic variables selected (i.e., direct effects). Age (agea) had a statistically significant relationship with PolEf. Looking at the fully standardized coefficients, it can be observed that one standard deviation increase in age resulted in 0.122 standard deviation decrease in political efficacy. Alternatively, looking at the standardized coefficients based on latent variables, holding all else equal (partial regression), one year increase in age was associated with 0.007 standard deviation decrease in PolEf, similarly to the previous results.

The relationship between PolEf and highest level of education (edllvdhu) was also significant. One standard deviation increase in education was associated with 0.121 standard deviation increase in PolEf.

The relationship between PolEf, income (hinctnta), feeling close to country and political orientation were all insignificant with negligible effect sizes. Gender was borderline significant, yet again, with tiny effects.

Regressing 'SatCSA' on the same predictor variables (i.e., sociodemographic factors' direct effect on SatCSA), painted a more nuanced picture. All relationships were significant except for education and gender. Holding all else equal, one standard deviation increase in age was associated with 0.117 standard deviation increase in SatCSA, or equivalently, one year increase in age, was associated with 0.007 standard deviation increase in SatCSA. One standard deviation increase in income was associated with 0.113, while being one standard deviation more to the right on the political spectrum with 0.381 standard deviation increase in SatCSA. Feeling close to one's country was reverse coded, therefore the results could be interpreted as follows: One standard deviation increase in 'fclcntr' (not feeling close to the country) resulted 0.159 standard deviation decrease in SatCSA, i.e., the closer an individual felt to their country the higher they scored on SatCSA.

The direct effect of SatCSA on PolEf was strong and significant. One standard deviation increase in SatCSA was associated with 0.684 standard deviation increase in PolEf, see figure A.30.

The indirect effects, i.e., the effect of select sociodemographic variables transmitted by the mediator variable, SatCSA, were insignificant for education and gender but were significant for age, income, feeling close to the country and political orientation, see figure A.31. The indirect effect of age on PolEf through SatCSA was positive and significant but rather small. The fully standardized regression coefficient was 0.080. The indirect effect of income was quite small too, with 1 standard deviation increase in the indirect effect of income having been associated with 0.077 standard deviation increase in PolEf. Positive regression coefficients here indicate that the predictors had positive relationships with SatCSA which in turn had a positive relationship with PolEf, conversely, negative coefficients indicate a negative relationship between the predictors and SatCSA which in turn transmits a negative effect to PolEf. The indirect effects of fclcntr and lrscale were also significant and their fully standardized effect sizes were more salient. (Not) feeling close to one's country (fclcntr is reverse coded) had a negative impact on SatCSA, which in turn resulted in a negative effect on PolEf. One standard deviation increase in the indirect effect of not feeling close to Hungary, resulted in 0.108 standard deviation decrease in PolEf, while one standard deviation increase in the indirect effect of political orientation (lrscale) resulted in 0.260 standard deviation increase in PolEf, indicating that being more to the right on the political spectrum had a positive effect on SatCSA which in turn mediated a positive effect to PolEf.

Total effects of age and gender were insignificant, effect sizes were negative and negligible, suggesting that age and gender did not significantly effect PolEf when considering both direct and indirect paths. On the other hand, total effects of education, income, (not) feeling close to the country and political orientation had significant total effects.

The direct effect of Education on PolEf was significant and positive, the indirect effect through SatSCA was non-significant. Nonetheless, Education in total, directly and indirectly through SatCSA, seem to have significantly increased Political Efficacy (0.028 + 0.121 = 0.149).

The indirect effects of Income through SatCSA was significant and positive. The direct effect was non-significant. The indirect effect accounted for most of the total effect (0.077 + 0.032 = 0.109). Income indirectly through SatCSA seem to have significantly increased Political Efficacy.

The direct effect of 'fclcntr' on PolEf was insignificant but the indirect effect through SatCSA was significant. The indirect effect accounted for most of the total effect (-0.012 - 0.108 = -0.120). 'fclcntr' indirectly through SatCSA seem to have significantly decreased Political Efficacy.

The indirect effects of Political Orientation through SatCSA was significant and positive. The direct effect was insignificant, negligible in size and negative. Therefore, the indirect effect accounted for most of the total effect (-0.030 + 0.260 = 0.230). Political orientation indirectly, through Trust, seemed to have significantly increased Political Efficacy.

4.1.3 Measurement equivalence

The purpose of the following section was to test measurement equivalence of Political Efficacy across genders. The strategy in doing so drew on the proposed procedure for equivalence testing by Meuleman and Billiet (2012) [19].

Different levels of measurement equivalence

First, configural invariance was tested to determine whether the factor structures were identical across different groups. It was examined whether the same items were loading on the same factors in both groups. This level of equivalence does not allow score comparability yet but it indicates that more or less the same concept is being measured across groups. However, at this stage, it has not yet been examined how this concept is mapped onto a measurement scale. This aspect required further stages of invariance testing.

The following step was testing for metric equivalence, which requires not only identical factor structures but equal factor loadings or slopes across groups as well. This level of invariance gives a bit more leverage to researchers for making comparisons. Once metric equivalence is established, it can be said, that one unit increase in the latent factor has the same meaning across groups. Comparing changes becomes possible. There still might be a bias in the mean structure, so one should not compare means yet. However, regression coefficients and all change measures become comparable.

Nonetheless, more often researchers are interested in comparing latent means, or the κ's. Scalar equivalence (or strong factorial invariance) tests whether the intercepts of indicator variables are equal across groups. Substantively, this means that persons across groups with latent factor score zero, will give exactly the same response to the observed variables, thus, full score comparability becomes possible. Responses depend on the latent factor only and not group membership.

Higher level equivalence tests exist but are less frequently used in practice. Strict invariance tests equality of indicator variances, meaning same amount of measurement error across groups. Structural invariance tests equality of factor variances, a necessary condition for comparing standardized coefficients [18].

Model fit

Table A.15 summarizes the fit measures of the invariance models fitted.

Configural fit was a simple CFA for the two groups, males and females. There was one latent factor, political efficacy (PolEf), five indicators (actrolg, cptppol, psppipl, psppsgv, and ptcpplt) of which 2 pairs were allowed to have error covariances (nactrolg ∼∼ cptppol and npsppsgv ∼∼ ptcpplt), yielding $5(5+1)/2 = 15$ pieces of information and $2{*}4{+}1 = 9$ unconstrained parameters (the variance of the latent factor and 4 factor loadings in each group) resulting in 6 degrees of freedom. CFI was 0.997, TLI 0.991, RMSEA 0.050 and SRMR 0.007, all indicating a very good fit. The χ^2 test was still significant with a p-value of 0.005 but the ratio of the test statistic and the degrees of freedom was just a bit over 3 with a score of 3.1285. Nonetheless, as mentioned, ANOVA tends to be overpowered as it is sensitive to large sample sizes and deviations from normality. Looking at the 'lavaan' output, it could be observed that the same indicators were loading heavily on the same factors.

Next metric invariance was assessed by putting equal factor loading constraints on the model. Meaning that the 4 unconstrained factor loadings in the 2 groups were set equal, therefore only 4 needed to be estimated instead of 8, and of course, the latent factor variance. This yielded 10 degrees of freedom, having gained 4 additional ones from the equality constraint $(5(5+1)/2-(4+1)=10)$. Again, model fit was excellent. CFI was 0.998, TLI 0.995, RMSEA 0.037and SRMR 0.012. The χ^2 test was significant with a p-value of 0.018. The ratio of the test statistic and the df was 2.1441, so below the commonly used threshold of 3. In the output, it could be observed that the non-standardized parameter estimates were set equal across groups. The latent factor means were set equal to zero in both groups for model identification purposes, therefore, the intercept values for observed variables actually reflect the average response of respondents. The average response of men on variable cptppol was 2.850 while women's 2.317.

At the level of scalar invariance, indicator intercepts were set equal as well, meaning an additional 4 degrees of freedom was gained (5 indicator intercepts were set equal, but the factor mean of the second groups had to be estimated). The χ^2 test was significant, but the alternative fit indices indicated a borderline reasonable to good fit. CFI, TLI and SRMR were 0.991 and 0.987 and 0.030 respectively, indicating an excellent fit. However RMSEA was somewhat above the desired level with 0.061. Strict and structural invariance models yielded similar model fits, as per table A.15.

Statistical Testing

The models were compared using χ^2 difference tests, a formal test (for nested models) to determine whether adding more constraints, moving to a higher level of invariance, significantly worsened model fit or not A.14. Invariance was achieved when there was a non-significant chi-square test result, the null hypothesis being that the more parsimonious model fits the data as well as the less parsimonious one. By definition, the more parsimonious model cannot fit the data better, at best, it can fit it as well as. When the p-value is non-significant a distance between the two models is negligible, thus the more parsimonious model is chosen. According to the ANOVA tests, as per table A.14, metric invariance has been reached but scalar has not. Nonetheless, as mentioned ANOVA uses χ^2 which is sensitive to departures from normality and large sample sizes, where it detects even small deviations. Other fit indices indicated a reasonable fit. Cheung, G.W. and Rensvold, R.B. recommended a cut-off point of 0.01 difference in the CFI between two competing models of measurement invariance [8]. Specifically, they argued, based on simulation studies, that a change of more than 0.01 in the CFI between the unconstrained and the constrained model would suggest a lack of invariance. As per table A.14, it can be observed that the difference in CFI was less than 0.01 across all five models. Therefore, it was concluded that comparing latent means was meaningful in the current scenario.

Results of measurement invariance testing

After establishing scalar invariance, latent means were compared. The reference group was 'Female'. Their latent factor intercept was set equal to zero. Political efficacy (PolEf) was positive in group 'Male', indicating that men had higher levels of political efficacy. The p-value was significant, meaning the result could be generalised. Furthermore, it was concluded, that men on average scored 0.107 standard deviation higher on political efficacy, see figures A.37 and A.36.

Partial Invariance

Based on the anova table, the null hypothesis that the scalar invariance model fits as well as the metric model should have been rejected. To err on the side of caution, it was further investigated whether a partial scalar invariant model could have been a better fit (MG approach). Using the lavTestScore() function in r, the effect of releasing equality constraints across groups was further explored. The first output, a Lagrange multiplier based multivariate score test score indicated that freeing all equality constraints would have resulted in an improved fit over the base model (global misfit). In this case we rejected the H0. The univariate score test of the second part gave the modification indices for all constrained parameters and indicated that relaxing the equality constraints between parameters p17 and p36 was going to result in the largest decrease in χ^2 value. These parameters related to psppsgv. The intercepts for psppsgv appeared to be significantly different across groups, suggesting that man and women answered differently at level zero of the latent factor, i.e., that gender influenced their response. In an iterative sequential process, freeing one constraint at a time partial scalar invariance was achieved by freeing intercept equality constraints on 3 variables, psppsgv, ptcpplt and psppipl. Fit indices and the χ^2 difference test results have been summarized in tables A.16 and A.17. In this model, the difference in PolEf between men and women was even more pronounced and significant, with men on average scoring 0.362 standard deviation higher than women. According to Byrne (1989), meaningful comparisons are possible as long as at least 2 items are equal across groups [5].

4.1.4 Multi-group SEM

Lastly, a multi-group SEM model was fit to test regression path invariance among genders in the previously fitted mediation model between Trust and Political Efficacy. First the unconstrained model was fit, then the constrained one, setting factor loadings equal across groups. In order to compare group specific effect sizes, direct and indirect effects, metric invariance was required. The fit indices and the χ^2 difference test results have been summarised in tables A.19 and A.18.

The unconstrained model had 88 degrees of freedom and the constrained 91. There was a small increase in χ^2 value, but only marginal. The two models had identical fit indices. CFI, TLI and SRMR were 0.97, 0.96 and 0.05 respectively, indicating sufficiently good fits. Nonetheless, the RMSEAs remained above the desired level, with 0.06. Overall, both models seemed to have reasonable fits. A χ^2 square difference test was conducted to compare them, which yielded an insignificant p-value, implying that the distance between the unconstrained and the constrained models was not statistically significant, confirming regression path invariance.

Conclusion

Trust, Satisfaction with the Current State of Affairs and Political Efficacy showed moderate to strong positive associations.

In the multiple indicators, multiple causes analysis, gender, highest level of education and age showed significant effects on Political Efficacy, with age being the least and gender the most salient.

The mediation analysis, in line with previous findings, found most sociodemographic factors to hold no significant direct effects over Political Efficacy or that they were negligible in size, only gender, education and age being statistically significant. Being a women was associated with scoring 0.122 standard deviation lower on Political Efficacy then men. Regressing sociodemographic variables on the mediators painted a more nuanced picture. All sociodemographic variables had significant effects on Trust and Satisfaction with the Current State of Affairs, except for age and gender, and education and gender, respectively.

Education, income, feeling close to the country, being more to the right on the political spectrum were all positively related to Trust, political orientation having the most salient effect. The total and the indirect effects transmitted by Trust to Political Efficacy were significant for education, income, feeling close to the country and political orientation. Higher income, higher education, feeling closer to the country and scoring more to the right on the political orientation scale were all associated with a positive total effect on Political Efficacy.

Age, income, feeling close to the country, being more to the right on the political spectrum were all positively related to Satisfaction with the Current State of Affairs, political orientation having the most salient effect, again. The indirect effects transmitted by Satisfaction with the Current State of Affairs to Political Efficacy were significant for age, income, feeling close to the country and political orientation. Total effects were significant for all, except age, meaning it did not significantly affect Political Efficacy when both paths considered. Education had significant direct and total effects but a non-significant indirect effect. Meaning, Satisfaction with the Current State of Affairs did not mediate the relationship between Education and Political Efficacy. Income, Feeling close to the country and Political Orientation on the other hand, all had significant indirect and total effects and non-significant directs effect. Indicating that Satisfaction with the Current State of Affairs facilitated the relationship between these variables and Political Efficacy. Older age, higher income, feeling closer to the country and scoring more to the right on the political orientation scale were all associated with a positive total effect on Political Efficacy.

The direct effect of Satisfaction with the Current State of Affairs and Trust on Political Efficacy were both strong and significant. Gender affected Political Efficacy only directly, the indirect paths were non-significant.

The χ^2 difference tests confirmed metric invariance of the selected items in measuring Political Efficacy across genders, however, scalar invariance was rejected. Nonetheless, these tests are known to be sensitive to large sample sizes and departures from normality. Other fit indices indicated appropriate fits and based on the criteria recommended by Cheung and Rensvold [8], the models even reached structural invariance. Therefore, it was concluded that comparing latent means was meaningful. Men on average scored 0.107 standard deviations higher on the latent factor Political Efficacy. The difference among genders was even more pronounced using the partial scalar invariance model, which suggested a 0.362 standard deviation difference among the two.

Regression path invariance was confirmed by the multi-group analysis as well.

Limitations of the current analysis include departures from multivariate-normality, violations of homoscedasticity assumptions and uncertainty regarding the nature of missingness (MAR or MNAR) in the data, to name but a few.

This topic seemed to have garnered relatively less academic attention in the Hungarian context so far, despite the country's unique sociopolitical landscape and the importance of the topic. The current paper attempted to get a better understanding of a subset of the complex interrelationships at play.

In terms of further research, a compelling area to explore could be gender and age differences in an international context with a specific comparative focus on Hungary. Furthermore, these differences might be more pronounced in certain subsets within age and gender groups. Focused information criteria (with maximum-likelihood estimation only) or multivariate clustering could possibly help further explore these differences and the underlying factors driving these variations in the data.

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Appendix

a Variables used

Table A.1: An overview of the variables used.

Variable	Type	Description
actrolg	11-point scale	Able to take active role in political group (0 Not at all able - 10 Completely able)
cptppol	11-point scale	Confident in own ability to participate in politics (0 Not at all confident - 10 Completely confident)
psppipl	11-point scale	Political system allows people to have influence on politics (0 Not at all - 10 Completely)
psppsgv	11-point scale	Political system allows people to have a say in what government does (0 Not at all - 10 Completely)
ptcpplt	11-point scale	Politicians care what people think (0 Not at all - 10 Completely)
stfeco	11-point scale	How satisfied with present state of economy in country (0 Extremely dissatisfied - 10 Extremely satisfied)
stfgov	11-point scale	How satisfied with the national government (0 Extremely dissatisfied - 10 Extremely satisfied)
stfdem	11-point scale	How satisfied with the way democracy works in country (0 Extremely dissatisfied - 10 Extremely satisfied)
stfedu	11-point scale	How satisfied with state of education in country nowadays (0 Extremely bad - 10 Extremely good)
stfhlth	11-point scale	How satisfied with state of health services in country nowadays (0 Extremely bad - 10 Extremely good)
pplfair	11-point scale	Most people try to take advantage of you, or try to be fair (0 Most people try to take advantage of me - 10 Most people try to be fair)
pplhlp	11-point scale	Most of the time people helpful or mostly looking out for themselves (0 People mostly look out for themselves - 10 People mostly try to be helpful)
ppltrst	11-point scale	(0 You can't be too careful - 10 Most people can be trusted)
trstlgl	11-point scale	Trust in the legal system (0 No trust at all - 10 Complete trust)
trstplc	11-point scale	Trust in the police (0 No trust at all - 10 Complete trust)
trstplt	11-point scale	Trust in politicians (0 No trust at all - 10 Complete trust)
trstep	11-point scale	Trust in the European Parliament (0 No trust at all - 10 Complete trust)
trstun	11-point scale	Trust in the United Nations (0 No trust at all - 10 Complete trust)
trstprt	11-point scale	Trust in political parties (0 No trust at all - 10 Complete trust)
trstprl	11-point scale	Trust in country's parliament (0 No trust at all - 10 Complete trust)
fclcntr	4-point scale	Feel close to country (1 Very close - 4 Not close at all)
lrscale	11-point scale	Placement on left right scale (0 Left - 10 Right)

Table A.1: An overview of the variables used.

Variable	Type	Description
gndr	Binary	Gender (1 Male - 2 Female)
agea	Integer	Age of respondent, calculated
hinctnta	Deciles	Income (1 1st decile - 10 10th decile)
eduyrs	Integer	Years of full-time education completed
edlvdhu	Ordered, 14 levels	(1 No formal education - 14 PhD)

b The most important model outputs

b.1 The measurement model

```
lavaan 0.6.15 ended normally after 95 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        70

  Number of observations                          1691
  Number of missing patterns                       154

Model Test User Model:

  Test statistic                               901.400
  Degrees of freedom                               160
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             22232.131
  Degrees of freedom                               190
  P-value                                        0.000
```

Figure A.1: The 'lavaan' output of the full measurement model.

```
Model Test Baseline Model:

  Test statistic                             22232.131
  Degrees of freedom                               190
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.966
  Tucker-Lewis Index (TLI)                       0.960

  Robust Comparative Fit Index (CFI)             0.966
  Robust Tucker-Lewis Index (TLI)                0.959

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -64527.553
  Loglikelihood unrestricted model (H1)     -64076.853

  Akaike (AIC)                              129195.106
  Bayesian (BIC)                            129575.422
  Sample-size adjusted Bayesian (SABIC)     129353.041

Root Mean Square Error of Approximation:

  RMSEA                                          0.052
  90 Percent confidence interval - lower         0.049
  90 Percent confidence interval - upper         0.056
  P-value H_0: RMSEA <= 0.050                    0.120
  P-value H_0: RMSEA >= 0.080                    0.000

  Robust RMSEA                                   0.054
  90 Percent confidence interval - lower         0.050
  90 Percent confidence interval - upper         0.057
  P-value H_0: Robust RMSEA <= 0.050             0.036
  P-value H_0: Robust RMSEA >= 0.080             0.000
```

Figure A.2: The 'lavaan' output of the full measurement model.

```
Standardized Root Mean Square Residual:

  SRMR                                           0.044

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust =~
    INSTT             1.000                               0.887    0.887
    IP                0.473    0.033   14.331    0.000    0.471    0.471
  SatCSA =~
    stfeco            1.000                               1.898    0.850
    stfgov            1.167    0.025   47.345    0.000    2.214    0.895
    stfdem            1.136    0.025   45.305    0.000    2.157    0.878
    stfedu            0.769    0.028   27.515    0.000    1.460    0.637
    stfhlth           0.754    0.029   26.227    0.000    1.431    0.597
  PolEf =~
    actrolg           1.000                               1.317    0.552
    cptppol           1.060    0.038   28.213    0.000    1.397    0.565
    psppipl           1.446    0.060   24.009    0.000    1.905    0.870
    psppsgv           1.490    0.063   23.505    0.000    1.963    0.853
    ptcpplt           1.476    0.063   23.259    0.000    1.944    0.854
  INSTT =~
    trstlgl           1.000                               2.013    0.789
    trstplc           0.819    0.024   33.970    0.000    1.648    0.652
    trstplt           1.043    0.028   37.206    0.000    2.099    0.848
    trstep            0.630    0.031   20.500    0.000    1.268    0.508
    trstun            0.579    0.031   18.830    0.000    1.165    0.473
    trstprt           0.950    0.028   34.168    0.000    1.911    0.795
    trstprl           1.110    0.027   40.484    0.000    2.234    0.889
  IP =~
    ppltrst           1.000                               1.793    0.759
    pplfair           0.904    0.039   23.148    0.000    1.620    0.721
    pplhlp            0.886    0.039   22.710    0.000    1.589    0.689
```

Figure A.3: The 'lavaan' output of the full measurement model.

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.trstplt ~~						
.trstprt	1.130	0.076	14.958	0.000	1.130	0.591
.trstep ~~						
.trstun	3.434	0.152	22.581	0.000	3.434	0.735
.trstlgl ~~						
.trstplc	1.108	0.092	11.985	0.000	1.108	0.369
.stfedu ~~						
.stfhlth	1.217	0.100	12.219	0.000	1.217	0.358
.actrolg ~~						
.cptppol	2.356	0.123	19.141	0.000	2.356	0.581
Trust ~~						
SatCSA	3.112	0.147	21.192	0.000	0.919	0.919
PolEf	1.678	0.108	15.520	0.000	0.714	0.714
SatCSA ~~						
PolEf	1.688	0.104	16.247	0.000	0.675	0.675

Figure A.4: The 'lavaan' output of the full measurement model.

Intercepts:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.stfeco	3.781	0.055	69.296	0.000	3.781	1.693
.stfgov	3.524	0.061	58.224	0.000	3.524	1.424
.stfdem	4.070	0.060	67.351	0.000	4.070	1.656
.stfedu	4.434	0.057	77.121	0.000	4.434	1.934
.stfhlth	3.352	0.058	57.309	0.000	3.352	1.397
.actrolg	2.221	0.058	38.116	0.000	2.221	0.931
.cptppol	2.545	0.061	42.006	0.000	2.545	1.030
.psppipl	2.182	0.053	40.819	0.000	2.182	0.996
.psppsgv	2.373	0.056	42.238	0.000	2.373	1.031
.ptcpplt	2.312	0.056	41.613	0.000	2.312	1.015
.trstlgl	4.618	0.062	74.184	0.000	4.618	1.811
.trstplc	5.325	0.062	86.481	0.000	5.325	2.106
.trstplt	2.944	0.060	48.779	0.000	2.944	1.190
.trstep	4.832	0.062	77.728	0.000	4.832	1.935
.trstun	5.310	0.062	85.697	0.000	5.310	2.155
.trstprt	2.955	0.059	50.313	0.000	2.955	1.229
.trstprl	3.841	0.061	62.619	0.000	3.841	1.529
.ppltrst	4.172	0.057	72.627	0.000	4.172	1.767
.pplfair	4.638	0.055	84.627	0.000	4.638	2.065
.pplhlp	4.357	0.056	77.678	0.000	4.357	1.889
Trust	0.000				0.000	0.000
SatCSA	0.000				0.000	0.000
PolEf	0.000				0.000	0.000
.INSTT	0.000				0.000	0.000
.IP	0.000				0.000	0.000

Figure A.5: The 'lavaan' output of the full measurement model.

```
Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .stfeco            1.388    0.062   22.499    0.000    1.388    0.278
   .stfgov            1.219    0.064   18.991    0.000    1.219    0.199
   .stfdem            1.389    0.069   20.255    0.000    1.389    0.230
   .stfedu            3.124    0.121   25.742    0.000    3.124    0.595
   .stfhlth           3.706    0.135   27.553    0.000    3.706    0.644
   .actrolg           3.956    0.144   27.387    0.000    3.956    0.695
   .cptppol           4.159    0.153   27.143    0.000    4.159    0.681
   .psppipl           1.168    0.062   18.747    0.000    1.168    0.243
   .psppsgv           1.442    0.071   20.454    0.000    1.442    0.272
   .ptcpplt           1.408    0.070   19.986    0.000    1.408    0.271
   .trstlgl           2.451    0.103   23.807    0.000    2.451    0.377
   .trstplc           3.676    0.138   26.554    0.000    3.676    0.575
   .trstplt           1.717    0.082   20.847    0.000    1.717    0.281
   .trstep            4.630    0.170   27.187    0.000    4.630    0.742
   .trstun            4.714    0.176   26.852    0.000    4.714    0.776
   .trstprt           2.130    0.093   22.881    0.000    2.130    0.368
   .trstprl           1.321    0.075   17.595    0.000    1.321    0.209
   .ppltrst           2.358    0.139   16.964    0.000    2.358    0.423
   .pplfair           2.420    0.125   19.329    0.000    2.420    0.480
   .pplhlp            2.793    0.132   21.128    0.000    2.793    0.525
    Trust             3.186    0.239   13.341    0.000    1.000    1.000
    SatCSA            3.602    0.170   21.144    0.000    1.000    1.000
    PolEf             1.735    0.148   11.690    0.000    1.000    1.000
   .INSTT             0.864    0.156    5.559    0.000    0.213    0.213
   .IP                2.501    0.170   14.710    0.000    0.778    0.778
```

Figure A.6: The 'lavaan' output of the full measurement model.

b.2 MIMIC models

Political Orientation

```
lavaan 0.6.15 ended normally after 102 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        71

                                                  Used       Total
  Number of observations                          1409        1691
  Number of missing patterns                        86

Model Test User Model:

  Test statistic                              1076.810
  Degrees of freedom                               179
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             19503.112
  Degrees of freedom                               210
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.953
  Tucker-Lewis Index (TLI)                       0.945

  Robust Comparative Fit Index (CFI)             0.953
  Robust Tucker-Lewis Index (TLI)                0.945
```

Figure A.7: The 'lavaan' output of the first MIMIC model, where latent variable Political Efficacy was regressed on Political Orientation.

```
Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)           -54044.008
  Loglikelihood unrestricted model (H1)   -53505.603

  Akaike (AIC)                            108230.015
  Bayesian (BIC)                          108602.811
  Sample-size adjusted Bayesian (SABIC)   108377.269

Root Mean Square Error of Approximation:

  RMSEA                                        0.060
  90 Percent confidence interval - lower       0.056
  90 Percent confidence interval - upper       0.063
  P-value H_0: RMSEA <= 0.050                  0.000
  P-value H_0: RMSEA >= 0.080                  0.000

  Robust RMSEA                                 0.060
  90 Percent confidence interval - lower       0.057
  90 Percent confidence interval - upper       0.064
  P-value H_0: Robust RMSEA <= 0.050           0.000
  P-value H_0: Robust RMSEA >= 0.080           0.000

Standardized Root Mean Square Residual:

  SRMR                                         0.074

Parameter Estimates:

  Standard errors                           Standard
  Information                               Observed
  Observed information based on              Hessian
```

Figure A.8: The 'lavaan' output of the first MIMIC model, where latent variable Political Efficacy was regressed on Political Orientation.

```
Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust =~
    INSTT             1.000                               0.900    0.900
    IP                0.471    0.036   13.092    0.000    0.473    0.473
  SatCSA =~
    stfeco            1.000                               1.906    0.861
    stfgov            1.187    0.026   46.149    0.000    2.263    0.904
    stfdem            1.128    0.026   43.702    0.000    2.151    0.882
    stfedu            0.799    0.029   27.744    0.000    1.524    0.673
    stfhlth           0.757    0.030   24.938    0.000    1.443    0.607
  PolEf =~
    actrolg           1.000                               1.288    0.538
    cptppol           1.070    0.042   25.250    0.000    1.379    0.559
    psppipl           1.500    0.070   21.384    0.000    1.932    0.870
    psppsgv           1.528    0.073   20.919    0.000    1.969    0.854
    ptcpplt           1.524    0.074   20.711    0.000    1.964    0.854
  INSTT =~
    trstlgl           1.000                               1.964    0.777
    trstplc           0.832    0.026   31.711    0.000    1.635    0.650
    trstplt           1.096    0.032   34.175    0.000    2.153    0.859
    trstep            0.593    0.034   17.649    0.000    1.164    0.478
    trstun            0.550    0.033   16.510    0.000    1.081    0.452
    trstprt           0.995    0.032   31.560    0.000    1.954    0.807
    trstprl           1.152    0.031   36.754    0.000    2.263    0.897
  IP =~
    ppltrst           1.000                               1.761    0.761
    pplfair           0.909    0.042   21.555    0.000    1.601    0.727
    pplhlp            0.892    0.043   20.893    0.000    1.571    0.691

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf ~
    lrscale           0.006    0.013    0.446    0.655    0.004    0.010
```

Figure A.9: The 'lavaan' output of the first MIMIC model, where latent variable Political Efficacy was regressed on Political Orientation.

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Trust ~~						
SatCSA	3.078	0.158	19.490	0.000	0.913	0.913
SatCSA ~~						
.PolEf	1.696	0.116	14.622	0.000	0.691	0.691
Trust ~~						
.PolEf	1.636	0.117	13.938	0.000	0.718	0.718
.trstplt ~~						
.trstprt	1.017	0.079	12.835	0.000	1.017	0.553
.trstep ~~						
.trstun	3.350	0.160	20.978	0.000	3.350	0.734
.trstlgl ~~						
.trstplc	1.239	0.101	12.234	0.000	1.239	0.406
.stfedu ~~						
.stfhlth	1.096	0.100	10.955	0.000	1.096	0.347
.actrolg ~~						
.cptppol	2.395	0.136	17.590	0.000	2.395	0.580

Figure A.10: The 'lavaan' output of the first MIMIC model, where latent variable Political Efficacy was regressed on Political Orientation.

Intercepts:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.stfeco	3.862	0.059	65.370	0.000	3.862	1.745
.stfgov	3.635	0.067	54.403	0.000	3.635	1.452
.stfdem	4.172	0.065	63.880	0.000	4.172	1.710
.stfedu	4.488	0.062	72.622	0.000	4.488	1.983
.stfhlth	3.423	0.063	53.934	0.000	3.423	1.440
.actrolg	2.357	0.093	25.327	0.000	2.357	0.984
.cptppol	2.683	0.098	27.397	0.000	2.683	1.088
.psppipl	2.283	0.117	19.448	0.000	2.283	1.028
.psppsgv	2.484	0.120	20.670	0.000	2.484	1.077
.ptcpplt	2.426	0.120	20.239	0.000	2.426	1.054
.trstlgl	4.711	0.067	69.809	0.000	4.711	1.863
.trstplc	5.380	0.067	80.176	0.000	5.380	2.138
.trstplt	3.080	0.067	46.064	0.000	3.080	1.228
.trstep	4.970	0.066	75.476	0.000	4.970	2.041
.trstun	5.396	0.065	82.700	0.000	5.396	2.256
.trstprt	3.112	0.065	48.162	0.000	3.112	1.285
.trstprl	3.917	0.067	58.211	0.000	3.917	1.553
.ppltrst	4.222	0.062	68.458	0.000	4.222	1.824
.pplfair	4.656	0.059	79.273	0.000	4.656	2.114
.pplhlp	4.372	0.061	72.201	0.000	4.372	1.923
Trust	0.000				0.000	0.000
SatCSA	0.000				0.000	0.000
.PolEf	0.000				0.000	0.000
.INSTT	0.000				0.000	0.000
.IP	0.000				0.000	0.000

Figure A.11: The 'lavaan' output of the first MIMIC model, where latent variable Political Efficacy was regressed on Political Orientation.

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.stfeco	1.267	0.061	20.679	0.000	1.267	0.259
.stfgov	1.145	0.066	17.446	0.000	1.145	0.183
.stfdem	1.325	0.069	19.192	0.000	1.325	0.223
.stfedu	2.801	0.119	23.630	0.000	2.801	0.547
.stfhlth	3.570	0.141	25.265	0.000	3.570	0.632
.actrolg	4.073	0.162	25.139	0.000	4.073	0.711
.cptppol	4.180	0.167	24.977	0.000	4.180	0.687
.psppipl	1.198	0.070	17.241	0.000	1.198	0.243
.psppsgv	1.442	0.077	18.821	0.000	1.442	0.271
.ptcpplt	1.436	0.078	18.349	0.000	1.436	0.271
.trstlgl	2.538	0.113	22.533	0.000	2.538	0.397
.trstplc	3.662	0.149	24.502	0.000	3.662	0.578
.trstplt	1.651	0.088	18.820	0.000	1.651	0.263
.trstep	4.576	0.181	25.272	0.000	4.576	0.771
.trstun	4.553	0.182	24.951	0.000	4.553	0.796
.trstprt	2.051	0.098	20.852	0.000	2.051	0.349
.trstprl	1.240	0.079	15.751	0.000	1.240	0.195
.ppltrst	2.254	0.145	15.574	0.000	2.254	0.421
.pplfair	2.287	0.130	17.625	0.000	2.287	0.472
.pplhlp	2.697	0.140	19.305	0.000	2.697	0.522
Trust	3.128	0.253	12.368	0.000	1.000	1.000
SatCSA	3.632	0.183	19.866	0.000	1.000	1.000
.PolEf	1.659	0.161	10.328	0.000	1.000	1.000
.INSTT	0.730	0.159	4.596	0.000	0.189	0.189
.IP	2.409	0.177	13.599	0.000	0.776	0.776

Figure A.12: The 'lavaan' output of the first MIMIC model, where latent variable Political Efficacy was regressed on Political Orientation.

Political Orientation and External Political Efficacy

```
Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust =~
    INSTT             1.000                               0.901    0.901
    IP                0.471    0.036   13.088    0.000    0.473    0.473
  SatCSA =~
    stfeco            1.000                               1.906    0.861
    stfgov            1.187    0.026   46.148    0.000    2.263    0.904
    stfdem            1.129    0.026   43.702    0.000    2.151    0.882
    stfedu            0.799    0.029   27.743    0.000    1.524    0.673
    stfhlth           0.757    0.030   24.937    0.000    1.442    0.607
  PolEf =~
    actrolg           1.000                               1.286    0.537
    cptppol           1.071    0.042   25.275    0.000    1.377    0.559
    psppipl           1.516    0.073   20.693    0.000    1.950    0.874
    psppsgv           1.531    0.076   20.165    0.000    1.968    0.854
    ptcpplt           1.514    0.076   19.943    0.000    1.946    0.850
  INSTT =~
    trstlgl           1.000                               1.964    0.777
    trstplc           0.832    0.026   31.711    0.000    1.635    0.650
    trstplt           1.096    0.032   34.174    0.000    2.153    0.859
    trstep            0.593    0.034   17.648    0.000    1.164    0.478
    trstun            0.550    0.033   16.510    0.000    1.081    0.452
    trstprt           0.995    0.032   31.559    0.000    1.954    0.807
    trstprl           1.152    0.031   36.755    0.000    2.263    0.897
  IP =~
    ppltrst           1.000                               1.761    0.761
    pplfair           0.909    0.042   21.555    0.000    1.601    0.727
    pplhlp            0.892    0.043   20.892    0.000    1.571    0.691

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf ~
    lrscale           0.012    0.024    0.488    0.625    0.009    0.021
  psppipl ~
    lrscale          -0.031    0.034   -0.910    0.363   -0.031   -0.032
  psppsgv ~
    lrscale          -0.008    0.035   -0.226    0.821   -0.008   -0.008
  ptcpplt ~
    lrscale           0.015    0.035    0.423    0.672    0.015    0.015
```

Figure A.13: The 'lavaan' output of the second MIMIC model, where latent variable Political Efficacy and indicator variables relating to External Political Efficacy were regressed on Political Orientation

Income

```
lavaan 0.6.15 ended normally after 101 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        71

                                                  Used       Total
  Number of observations                          1204        1691
  Number of missing patterns                       106

Model Test User Model:

  Test statistic                               922.218
  Degrees of freedom                               179
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             16209.443
  Degrees of freedom                               210
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.954
  Tucker-Lewis Index (TLI)                       0.946

  Robust Comparative Fit Index (CFI)             0.953
  Robust Tucker-Lewis Index (TLI)                0.945

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -46021.269
  Loglikelihood unrestricted model (H1)     -45560.160

  Akaike (AIC)                               92184.538
  Bayesian (BIC)                             92546.169
  Sample-size adjusted Bayesian (SABIC)      92320.645

Root Mean Square Error of Approximation:

  RMSEA                                          0.059
  90 Percent confidence interval - lower         0.055
  90 Percent confidence interval - upper         0.063
```

Figure A.14: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income

```
  P-value H_0: RMSEA <= 0.050                    0.000
  P-value H_0: RMSEA >= 0.080                    0.000

  Robust RMSEA                                   0.060
  90 Percent confidence interval - lower         0.056
  90 Percent confidence interval - upper         0.064
  P-value H_0: Robust RMSEA <= 0.050             0.000
  P-value H_0: Robust RMSEA >= 0.080             0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.061

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian
```

Figure A.15: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income

```
Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust =~
    INSTT             1.000                               0.941    0.941
    IP                0.479    0.038   12.682    0.000    0.488    0.488
  SatCSA =~
    stfeco            1.000                               1.916    0.851
    stfgov            1.166    0.029   40.364    0.000    2.234    0.895
    stfdem            1.136    0.029   39.498    0.000    2.176    0.887
    stfedu            0.779    0.032   24.068    0.000    1.493    0.652
    stfhlth           0.740    0.034   21.593    0.000    1.418    0.582
  PolEf =~
    actrolg           1.000                               1.370    0.580
    cptppol           1.032    0.041   25.091    0.000    1.413    0.583
    psppipl           1.345    0.063   21.524    0.000    1.843    0.851
    psppsgv           1.417    0.067   21.165    0.000    1.940    0.846
    ptcpplt           1.409    0.068   20.818    0.000    1.930    0.846
  INSTT =~
    trstlgl           1.000                               1.984    0.791
    trstplc           0.815    0.030   27.329    0.000    1.617    0.644
    trstplt           1.087    0.034   32.106    0.000    2.156    0.857
    trstep            0.632    0.037   17.201    0.000    1.254    0.502
    trstun            0.552    0.036   15.201    0.000    1.096    0.452
    trstprt           0.977    0.034   29.112    0.000    1.938    0.795
    trstprl           1.118    0.033   34.336    0.000    2.217    0.886
  IP =~
    ppltrst           1.000                               1.833    0.788
    pplfair           0.888    0.043   20.790    0.000    1.628    0.735
    pplhlp            0.860    0.043   20.092    0.000    1.577    0.681

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf ~
    hinctnta          0.049    0.012    3.988    0.000    0.036    0.097
```

Figure A.16: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Trust ~~						
SatCSA	3.145	0.174	18.082	0.000	0.880	0.880
SatCSA ~~						
.PolEf	1.760	0.125	14.105	0.000	0.674	0.674
Trust ~~						
.PolEf	1.808	0.132	13.714	0.000	0.711	0.711
.trstplt ~~						
.trstprt	1.023	0.088	11.687	0.000	1.023	0.534
.trstep ~~						
.trstun	3.422	0.179	19.122	0.000	3.422	0.734
.trstlgl ~~						
.trstplc	0.929	0.105	8.880	0.000	0.929	0.315
.stfedu ~~						
.stfhlth	1.249	0.119	10.469	0.000	1.249	0.363
.actrolg ~~						
.cptppol	2.145	0.137	15.646	0.000	2.145	0.567

Intercepts:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.stfeco	3.783	0.065	58.081	0.000	3.783	1.680
.stfgov	3.573	0.072	49.436	0.000	3.573	1.430
.stfdem	4.140	0.071	58.030	0.000	4.140	1.688
.stfedu	4.552	0.068	66.937	0.000	4.552	1.988
.stfhlth	3.456	0.070	49.104	0.000	3.456	1.419
.actrolg	1.918	0.104	18.456	0.000	1.918	0.813
.cptppol	2.206	0.107	20.577	0.000	2.206	0.910
.psppipl	1.884	0.121	15.510	0.000	1.884	0.871
.psppsgv	2.039	0.128	15.908	0.000	2.039	0.889
.ptcpplt	1.994	0.127	15.677	0.000	1.994	0.874
.trstlgl	4.790	0.073	66.029	0.000	4.790	1.910
.trstplc	5.461	0.072	75.364	0.000	5.461	2.175
.trstplt	3.067	0.073	42.195	0.000	3.067	1.219
.trstep	5.036	0.074	68.406	0.000	5.036	2.017
.trstun	5.553	0.072	76.913	0.000	5.553	2.293
.trstprt	3.062	0.070	43.469	0.000	3.062	1.257
.trstprl	3.988	0.072	55.068	0.000	3.988	1.593
.ppltrst	4.219	0.067	62.905	0.000	4.219	1.814
.pplfair	4.643	0.064	72.566	0.000	4.643	2.097
.pplhlp	4.364	0.067	65.336	0.000	4.364	1.883
Trust	0.000				0.000	0.000
SatCSA	0.000				0.000	0.000
.PolEf	0.000				0.000	0.000

Figure A.17: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.stfeco	1.394	0.073	19.090	0.000	1.394	0.275
.stfgov	1.247	0.076	16.354	0.000	1.247	0.200
.stfdem	1.281	0.077	16.722	0.000	1.281	0.213
.stfedu	3.014	0.139	21.658	0.000	3.014	0.575
.stfhlth	3.924	0.168	23.393	0.000	3.924	0.661
.actrolg	3.696	0.162	22.858	0.000	3.696	0.663
.cptppol	3.876	0.171	22.681	0.000	3.876	0.660
.psppipl	1.288	0.078	16.593	0.000	1.288	0.275
.psppsgv	1.498	0.087	17.255	0.000	1.498	0.285
.ptcpplt	1.480	0.088	16.846	0.000	1.480	0.284
.trstlgl	2.355	0.116	20.240	0.000	2.355	0.374
.trstplc	3.691	0.163	22.606	0.000	3.691	0.585
.trstplt	1.682	0.096	17.468	0.000	1.682	0.266
.trstep	4.660	0.202	23.047	0.000	4.660	0.748
.trstun	4.665	0.205	22.751	0.000	4.665	0.795
.trstprt	2.181	0.112	19.557	0.000	2.181	0.367
.trstprl	1.351	0.087	15.592	0.000	1.351	0.216
.ppltrst	2.051	0.153	13.391	0.000	2.051	0.379
.pplfair	2.252	0.138	16.274	0.000	2.252	0.459
.pplhlp	2.883	0.154	18.723	0.000	2.883	0.537
Trust	3.482	0.286	12.175	0.000	1.000	1.000
SatCSA	3.673	0.205	17.958	0.000	1.000	1.000
.PolEf	1.858	0.177	10.525	0.000	0.991	0.991
.INSTT	0.452	0.173	2.618	0.009	0.115	0.115
.IP	2.560	0.196	13.050	0.000	0.762	0.762

Figure A.18: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income

Income and Feeling Close to Country

```
lavaan 0.6.15 ended normally after 100 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        72

                                                  Used       Total
  Number of observations                          1202        1691
  Number of missing patterns                       106

Model Test User Model:

  Test statistic                              1006.771
  Degrees of freedom                               198
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             16280.372
  Degrees of freedom                               230
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.950
  Tucker-Lewis Index (TLI)                       0.941

  Robust Comparative Fit Index (CFI)             0.949
  Robust Tucker-Lewis Index (TLI)                0.941

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -45951.056
  Loglikelihood unrestricted model (H1)     -45447.670

  Akaike (AIC)                               92046.112
  Bayesian (BIC)                             92412.717
  Sample-size adjusted Bayesian (SABIC)      92184.017
```

Figure A.19: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income and Feeling Close to One's Country

```
Root Mean Square Error of Approximation:

  RMSEA                                          0.058
  90 Percent confidence interval - lower         0.055
  90 Percent confidence interval - upper         0.062
  P-value H_0: RMSEA <= 0.050                    0.000
  P-value H_0: RMSEA >= 0.080                    0.000

  Robust RMSEA                                   0.060
  90 Percent confidence interval - lower         0.056
  90 Percent confidence interval - upper         0.063
  P-value H_0: Robust RMSEA <= 0.050             0.000
  P-value H_0: Robust RMSEA >= 0.080             0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.067

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust =~
    INSTT             1.000                               0.940    0.940
    IP                0.481    0.038   12.711    0.000    0.488    0.488
  SatCSA =~
    stfeco            1.000                               1.919    0.852
    stfgov            1.165    0.029   40.409    0.000    2.236    0.894
    stfdem            1.134    0.029   39.550    0.000    2.177    0.887
    stfedu            0.778    0.032   24.078    0.000    1.494    0.652
    stfhlth           0.739    0.034   21.594    0.000    1.419    0.582
  PolEf =~
    actrolg           1.000                               1.379    0.583
    cptppol           1.032    0.041   25.076    0.000    1.424    0.586
    psppipl           1.345    0.062   21.520    0.000    1.855    0.853
    psppsgv           1.415    0.067   21.164    0.000    1.952    0.847
    ptcpplt           1.409    0.068   20.817    0.000    1.943    0.847
  INSTT =~
    trstlgl           1.000                               1.984    0.791
    trstplc           0.815    0.030   27.301    0.000    1.617    0.644
    trstplt           1.087    0.034   32.076    0.000    2.156    0.857
    trstep            0.632    0.037   17.184    0.000    1.254    0.502
    trstun            0.552    0.036   15.166    0.000    1.095    0.452
    trstprt           0.977    0.034   29.081    0.000    1.938    0.795
    trstprl           1.118    0.033   34.316    0.000    2.218    0.886
  IP =~
    ppltrst           1.000                               1.836    0.789
    pplfair           0.888    0.043   20.820    0.000    1.630    0.736
    pplhlp            0.859    0.043   20.095    0.000    1.578    0.680
```

Figure A.20: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income and Feeling Close to One's Country

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf ~
    hinctnta          0.047    0.012    3.832    0.000    0.034    0.093
    fclcntr           0.105    0.053    1.990    0.047    0.076    0.047

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust ~~
    SatCSA            3.151    0.174   18.075    0.000    0.880    0.880
  SatCSA ~~
   .PolEf             1.788    0.127   14.098    0.000    0.679    0.679
  Trust ~~
   .PolEf             1.838    0.134   13.695    0.000    0.719    0.719
 .trstplt ~~
   .trstprt           1.024    0.088   11.686    0.000    1.024    0.534
 .trstep ~~
   .trstun            3.430    0.179   19.116    0.000    3.430    0.734
 .trstlgl ~~
   .trstplc           0.931    0.105    8.884    0.000    0.931    0.316
 .stfedu ~~
   .stfhlth           1.251    0.120   10.467    0.000    1.251    0.363
 .actrolg ~~
   .cptppol           2.142    0.137   15.614    0.000    2.142    0.566

Intercepts:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .stfeco            3.781    0.065   57.991    0.000    3.781    1.679
   .stfgov            3.573    0.072   49.369    0.000    3.573    1.429
   .stfdem            4.142    0.071   57.970    0.000    4.142    1.687
   .stfedu            4.553    0.068   66.910    0.000    4.553    1.988
   .stfhlth           3.459    0.070   49.071    0.000    3.459    1.419
   .actrolg           1.770    0.127   13.915    0.000    1.770    0.748
   .cptppol           2.052    0.131   15.646    0.000    2.052    0.845
   .psppipl           1.688    0.155   10.870    0.000    1.688    0.776
   .psppsgv           1.834    0.164   11.204    0.000    1.834    0.796
   .ptcpplt           1.789    0.163   11.002    0.000    1.789    0.780
   .trstlgl           4.794    0.073   66.021    0.000    4.794    1.911
   .trstplc           5.464    0.073   75.303    0.000    5.464    2.175
   .trstplt           3.070    0.073   42.197    0.000    3.070    1.220
   .trstep            5.036    0.074   68.287    0.000    5.036    2.016
   .trstun            5.555    0.072   76.846    0.000    5.555    2.293
   .trstprt           3.064    0.071   43.450    0.000    3.064    1.257
   .trstprl           3.991    0.072   55.043    0.000    3.991    1.594
   .ppltrst           4.217    0.067   62.787    0.000    4.217    1.812
   .pplfair           4.646    0.064   72.522    0.000    4.646    2.098
   .pplhlp            4.364    0.067   65.226    0.000    4.364    1.881
    Trust             0.000                               0.000    0.000
    SatCSA            0.000                               0.000    0.000
   .PolEf             0.000                               0.000    0.000
   .INSTT             0.000                               0.000    0.000
   .IP                0.000                               0.000    0.000
```

Figure A.21: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income and Feeling Close to One's Country

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.stfeco	1.387	0.073	19.039	0.000	1.387	0.274
.stfgov	1.250	0.076	16.369	0.000	1.250	0.200
.stfdem	1.284	0.077	16.729	0.000	1.284	0.213
.stfedu	3.015	0.139	21.655	0.000	3.015	0.575
.stfhlth	3.928	0.168	23.375	0.000	3.928	0.661
.actrolg	3.695	0.162	22.837	0.000	3.695	0.660
.cptppol	3.875	0.171	22.659	0.000	3.875	0.657
.psppipl	1.291	0.078	16.593	0.000	1.291	0.273
.psppsgv	1.500	0.087	17.256	0.000	1.500	0.282
.ptcpplt	1.482	0.088	16.839	0.000	1.482	0.282
.trstlgl	2.356	0.116	20.230	0.000	2.356	0.375
.trstplc	3.695	0.164	22.592	0.000	3.695	0.586
.trstplt	1.682	0.096	17.463	0.000	1.682	0.266
.trstep	4.669	0.203	23.027	0.000	4.669	0.748
.trstun	4.673	0.206	22.734	0.000	4.673	0.796
.trstprt	2.184	0.112	19.553	0.000	2.184	0.368
.trstprl	1.351	0.087	15.579	0.000	1.351	0.215
.ppltrst	2.046	0.153	13.351	0.000	2.046	0.378
.pplfair	2.250	0.138	16.259	0.000	2.250	0.459
.pplhlp	2.889	0.154	18.731	0.000	2.889	0.537
Trust	3.478	0.286	12.178	0.000	1.000	1.000
SatCSA	3.684	0.205	17.976	0.000	1.000	1.000
.PolEf	1.882	0.179	10.502	0.000	0.989	0.989
.INSTT	0.456	0.172	2.651	0.008	0.116	0.116
.IP	2.567	0.196	13.064	0.000	0.761	0.761

Figure A.22: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income and Feeling Close to One's Country

Income, Age and Education

```
lavaan 0.6.15 ended normally after 110 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        73

                                                  Used       Total
  Number of observations                          1203        1691
  Number of missing patterns                       105

Model Test User Model:

  Test statistic                              1069.897
  Degrees of freedom                               217
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             16392.735
  Degrees of freedom                               250
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.947
  Tucker-Lewis Index (TLI)                       0.939

  Robust Comparative Fit Index (CFI)             0.947
  Robust Tucker-Lewis Index (TLI)                0.938

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -45972.835
  Loglikelihood unrestricted model (H1)     -45437.886

  Akaike (AIC)                               92091.670
  Bayesian (BIC)                             92463.427
  Sample-size adjusted Bayesian (SABIC)      92231.551

Root Mean Square Error of Approximation:

  RMSEA                                          0.057
  90 Percent confidence interval - lower         0.054
  90 Percent confidence interval - upper         0.061
  P-value H_0: RMSEA <= 0.050                    0.000
  P-value H_0: RMSEA >= 0.080                    0.000

  Robust RMSEA                                   0.058
  90 Percent confidence interval - lower         0.055
  90 Percent confidence interval - upper         0.062
  P-value H_0: Robust RMSEA <= 0.050             0.000
  P-value H_0: Robust RMSEA >= 0.080             0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.066
```

Figure A.23: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income, Age and Education

```
Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust =~
    INSTT             1.000                               0.946    0.946
    IP                0.474    0.038   12.574    0.000    0.486    0.486
  SatCSA =~
    stfeco            1.000                               1.916    0.851
    stfgov            1.166    0.029   40.352    0.000    2.233    0.894
    stfdem            1.135    0.029   39.505    0.000    2.175    0.887
    stfedu            0.781    0.032   24.104    0.000    1.496    0.653
    stfhlth           0.741    0.034   21.598    0.000    1.419    0.582
  PolEf =~
    actrolg           1.000                               1.374    0.583
    cptppol           1.035    0.041   25.281    0.000    1.423    0.588
    psppipl           1.337    0.062   21.655    0.000    1.838    0.850
    psppsgv           1.408    0.066   21.301    0.000    1.936    0.845
    ptcpplt           1.401    0.067   20.963    0.000    1.926    0.845
  INSTT =~
    trstlgl           1.000                               1.985    0.791
    trstplc           0.816    0.030   27.342    0.000    1.619    0.645
    trstplt           1.086    0.034   32.107    0.000    2.156    0.857
    trstep            0.632    0.037   17.204    0.000    1.254    0.502
    trstun            0.553    0.036   15.216    0.000    1.097    0.453
    trstprt           0.976    0.034   29.108    0.000    1.937    0.795
    trstprl           1.117    0.033   34.327    0.000    2.217    0.885
  IP =~
    ppltrst           1.000                               1.833    0.788
    pplfair           0.888    0.043   20.772    0.000    1.628    0.735
    pplhlp            0.861    0.043   20.079    0.000    1.579    0.681

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf ~
    hinctnta          0.017    0.013    1.348    0.178    0.013    0.034
    agea             -0.008    0.002   -4.068    0.000   -0.005   -0.099
    edlvdhu           0.057    0.012    4.565    0.000    0.041    0.116
```

Figure A.24: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income, Age and Education

```
Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Trust ~~
    SatCSA            3.149    0.174   18.088    0.000    0.875    0.875
  SatCSA ~~
   .PolEf             1.768    0.125   14.193    0.000    0.682    0.682
  Trust ~~
   .PolEf             1.801    0.131   13.737    0.000    0.709    0.709
 .trstplt ~~
   .trstprt           1.023    0.088   11.682    0.000    1.023    0.534
 .trstep ~~
   .trstun            3.423    0.179   19.110    0.000    3.423    0.734
 .trstlgl ~~
   .trstplc           0.925    0.105    8.842    0.000    0.925    0.314
 .stfedu ~~
   .stfhlth           1.247    0.119   10.445    0.000    1.247    0.363
 .actrolg ~~
   .cptppol           2.119    0.136   15.570    0.000    2.119    0.564

Intercepts:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .stfeco            3.781    0.065   58.053    0.000    3.781    1.680
   .stfgov            3.570    0.072   49.407    0.000    3.570    1.430
   .stfdem            4.137    0.071   58.015    0.000    4.137    1.688
   .stfedu            4.552    0.068   66.890    0.000    4.552    1.987
   .stfhlth           3.455    0.070   49.051    0.000    3.455    1.418
   .actrolg           2.188    0.159   13.747    0.000    2.188    0.927
   .cptppol           2.483    0.165   15.079    0.000    2.483    1.025
   .psppipl           2.244    0.202   11.100    0.000    2.244    1.038
   .psppsgv           2.417    0.213   11.346    0.000    2.417    1.055
   .ptcpplt           2.371    0.212   11.188    0.000    2.371    1.041
   .trstlgl           4.790    0.073   65.975    0.000    4.790    1.909
   .trstplc           5.461    0.073   75.306    0.000    5.461    2.174
   .trstplt           3.065    0.073   42.149    0.000    3.065    1.218
   .trstep            5.036    0.074   68.356    0.000    5.036    2.017
   .trstun            5.553    0.072   76.862    0.000    5.553    2.292
   .trstprt           3.060    0.070   43.423    0.000    3.060    1.256
   .trstprl           3.987    0.072   55.018    0.000    3.987    1.592
   .ppltrst           4.220    0.067   62.876    0.000    4.220    1.814
   .pplfair           4.645    0.064   72.544    0.000    4.645    2.097
   .pplhlp            4.364    0.067   65.287    0.000    4.364    1.882
    Trust             0.000                               0.000    0.000
    SatCSA            0.000                               0.000    0.000
   .PolEf             0.000                               0.000    0.000
   .INSTT             0.000                               0.000    0.000
   .IP                0.000                               0.000    0.000
```

Figure A.25: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income, Age and Education

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.stfeco	1.395	0.073	19.107	0.000	1.395	0.275
.stfgov	1.250	0.076	16.401	0.000	1.250	0.200
.stfdem	1.277	0.076	16.727	0.000	1.277	0.213
.stfedu	3.011	0.139	21.646	0.000	3.011	0.574
.stfhlth	3.924	0.168	23.384	0.000	3.924	0.661
.actrolg	3.676	0.161	22.838	0.000	3.676	0.661
.cptppol	3.842	0.170	22.657	0.000	3.842	0.655
.psppipl	1.295	0.077	16.730	0.000	1.295	0.277
.psppsgv	1.502	0.087	17.340	0.000	1.502	0.286
.ptcpplt	1.481	0.087	16.942	0.000	1.481	0.285
.trstlgl	2.354	0.116	20.220	0.000	2.354	0.374
.trstplc	3.688	0.163	22.588	0.000	3.688	0.584
.trstplt	1.682	0.096	17.457	0.000	1.682	0.266
.trstep	4.663	0.202	23.036	0.000	4.663	0.748
.trstun	4.666	0.205	22.740	0.000	4.666	0.795
.trstprt	2.182	0.112	19.554	0.000	2.182	0.368
.trstprl	1.356	0.087	15.614	0.000	1.356	0.216
.ppltrst	2.055	0.153	13.399	0.000	2.055	0.380
.pplfair	2.253	0.139	16.260	0.000	2.253	0.459
.pplhlp	2.883	0.154	18.697	0.000	2.883	0.536
Trust	3.529	0.289	12.194	0.000	1.000	1.000
SatCSA	3.670	0.204	17.955	0.000	1.000	1.000
.PolEf	1.829	0.173	10.589	0.000	0.968	0.968
.INSTT	0.411	0.176	2.342	0.019	0.104	0.104
.IP	2.567	0.197	13.046	0.000	0.764	0.764

Figure A.26: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income, Age and Education

Income, Age, Gender

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PolEf ~						
hinctnta	0.034	0.012	2.775	0.006	0.025	0.068
agea	-0.008	0.002	-4.219	0.000	-0.006	-0.102
gndr	-0.145	0.065	-2.233	0.026	-0.105	-0.052

Figure A.27: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income, Age, Gender

Income, Age, Highest Level of Education, Feeling Close to Country and Gender

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PolEf ~						
hinctnta	0.014	0.013	1.103	0.270	0.010	0.028
agea	-0.007	0.002	-3.573	0.000	-0.005	-0.090
edlvdhu	0.060	0.012	4.826	0.000	0.044	0.123
fclcntr	0.039	0.055	0.723	0.470	0.029	0.018
gndr	-0.171	0.065	-2.617	0.009	-0.124	-0.061

Figure A.28: The 'lavaan' output of a MIMIC model, where latent variable Political Efficacy was regressed on Income, Age, Highest Level of Education, Feeling Close to Country and Gender

b.3 Mediation models

SatCSA

```
lavaan 0.6.15 ended normally after 89 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        45

                                                  Used       Total
  Number of observations                          1035        1691
  Number of missing patterns                        37

Model Test User Model:

  Test statistic                               407.543
  Degrees of freedom                                80
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              7300.213
  Degrees of freedom                               105
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.954
  Tucker-Lewis Index (TLI)                       0.940

  Robust Comparative Fit Index (CFI)             0.955
  Robust Tucker-Lewis Index (TLI)                0.940

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -19616.718
  Loglikelihood unrestricted model (H1)     -19412.947

  Akaike (AIC)                               39323.436
  Bayesian (BIC)                             39545.833
  Sample-size adjusted Bayesian (SABIC)      39402.908
```

Figure A.29: The 'lavaan' output of a mediation model between SatCSA and Political Efficacy

```
  Robust RMSEA                                   0.064
  90 Percent confidence interval - lower         0.057
  90 Percent confidence interval - upper         0.070
  P-value H_0: Robust RMSEA <= 0.050             0.000
  P-value H_0: Robust RMSEA >= 0.080             0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.041

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf =~
    actrolg           1.000                               1.400    0.588
    cptppol           1.029    0.044   23.368    0.000    1.440    0.592
    psppipl           1.357    0.067   20.263    0.000    1.900    0.862
    psppsgv           1.402    0.071   19.770    0.000    1.963    0.852
    ptcpplt           1.392    0.072   19.444    0.000    1.949    0.842
  SatCSA =~
    stfeco            1.000                               1.928    0.865
    stfgov            1.180    0.030   39.418    0.000    2.276    0.902
    stfdem            1.127    0.030   38.136    0.000    2.172    0.890
    stfedu            0.783    0.034   23.365    0.000    1.509    0.666
    stfhlth           0.730    0.036   20.393    0.000    1.408    0.585

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf ~
    agea       (c)   -0.010    0.002   -4.311    0.000   -0.007   -0.122
    edlvdhu   (c1)    0.061    0.014    4.373    0.000    0.044    0.121
    hinctnta  (c2)    0.016    0.014    1.137    0.255    0.012    0.032
    gndr      (c3)   -0.151    0.073   -2.067    0.039   -0.108   -0.053
    fclcntr   (c4)   -0.026    0.060   -0.438    0.661   -0.019   -0.012
    lrscale   (c5)   -0.019    0.017   -1.086    0.278   -0.013   -0.031
  SatCSA ~
    agea       (a)    0.013    0.004    3.615    0.000    0.007    0.117
    edlvdhu   (a1)    0.029    0.022    1.297    0.194    0.015    0.041
    hinctnta  (a2)    0.081    0.023    3.496    0.000    0.042    0.113
    gndr      (a3)    0.098    0.116    0.844    0.399    0.051    0.025
    fclcntr   (a4)   -0.493    0.096   -5.150    0.000   -0.256   -0.159
    lrscale   (a5)    0.321    0.026   12.324    0.000    0.167    0.381
  PolEf ~
    SatCSA     (b)    0.496    0.031   15.843    0.000    0.684    0.684

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .actrolg ~~
   .cptppol           2.110    0.147   14.350    0.000    2.110    0.558
 .stfedu ~~
   .stfhlth           1.238    0.123   10.079    0.000    1.238    0.375
```

Figure A.30: The 'lavaan' output of a mediation model between SatCSA and Political Efficacy

Intercepts:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.actrolg	1.579	0.327	4.833	0.000	1.579	0.663
.cptppol	1.864	0.336	5.547	0.000	1.864	0.766
.psppipl	1.330	0.435	3.055	0.002	1.330	0.603
.psppsgv	1.476	0.451	3.276	0.001	1.476	0.641
.ptcpplt	1.432	0.447	3.200	0.001	1.432	0.619
.stfeco	1.389	0.422	3.291	0.001	1.389	0.624
.stfgov	0.753	0.497	1.516	0.130	0.753	0.298
.stfdem	1.440	0.474	3.035	0.002	1.440	0.590
.stfedu	2.669	0.338	7.885	0.000	2.669	1.177
.stfhlth	1.716	0.320	5.355	0.000	1.716	0.713
.PolEf	0.000				0.000	0.000
.SatCSA	0.000				0.000	0.000

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.actrolg	3.707	0.175	21.204	0.000	3.707	0.654
.cptppol	3.852	0.183	21.085	0.000	3.852	0.650
.psppipl	1.253	0.083	15.079	0.000	1.253	0.258
.psppsgv	1.457	0.091	15.990	0.000	1.457	0.274
.ptcpplt	1.559	0.096	16.223	0.000	1.559	0.291
.stfeco	1.245	0.073	17.085	0.000	1.245	0.251
.stfgov	1.180	0.082	14.467	0.000	1.180	0.186
.stfdem	1.233	0.081	15.281	0.000	1.233	0.207
.stfedu	2.865	0.142	20.242	0.000	2.865	0.557
.stfhlth	3.812	0.176	21.696	0.000	3.812	0.658
.PolEf	0.967	0.105	9.238	0.000	0.494	0.494
.SatCSA	2.996	0.177	16.920	0.000	0.806	0.806

Defined Parameters:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ab_age	0.006	0.002	3.539	0.000	0.005	0.080
a1b_edl	0.014	0.011	1.294	0.196	0.010	0.028
a2b_inco	0.040	0.012	3.427	0.001	0.029	0.077
a3b_gndr	0.049	0.058	0.842	0.400	0.035	0.017
a4b_fclcntr	-0.245	0.050	-4.929	0.000	-0.175	-0.108
a5b_lrscale	0.159	0.016	9.992	0.000	0.114	0.260
total_age	-0.003	0.003	-1.251	0.211	-0.002	-0.042
total1_edl	0.075	0.017	4.390	0.000	0.054	0.149
total2_inco	0.056	0.018	3.183	0.001	0.040	0.109
total3_gndr	-0.102	0.089	-1.140	0.254	-0.073	-0.036
total4_fclcntr	-0.271	0.074	-3.674	0.000	-0.194	-0.120
total5_lrscale	0.141	0.020	6.890	0.000	0.100	0.230

Figure A.31: The 'lavaan' output of a mediation model between SatCSA and Political Efficacy

Trust

```
lavaan 0.6.15 ended normally after 118 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        64

                                                  Used       Total
  Number of observations                          1035        1691
  Number of missing patterns                        34

Model Test User Model:

  Test statistic                               660.878
  Degrees of freedom                               161
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             10284.733
  Degrees of freedom                               195
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.950
  Tucker-Lewis Index (TLI)                       0.940

  Robust Comparative Fit Index (CFI)             0.950
  Robust Tucker-Lewis Index (TLI)                0.940

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -30169.307
  Loglikelihood unrestricted model (H1)     -29838.868

  Akaike (AIC)                               60466.613
  Bayesian (BIC)                             60782.911
  Sample-size adjusted Bayesian (SABIC)      60579.640

Root Mean Square Error of Approximation:

  RMSEA                                          0.055
  90 Percent confidence interval - lower         0.050
  90 Percent confidence interval - upper         0.059
  P-value H_0: RMSEA <= 0.050                    0.034
  P-value H_0: RMSEA >= 0.080                    0.000

  Robust RMSEA                                   0.055
  90 Percent confidence interval - lower         0.051
  90 Percent confidence interval - upper         0.060
  P-value H_0: Robust RMSEA <= 0.050             0.023
  P-value H_0: Robust RMSEA >= 0.080             0.000
```

Figure A.32: The 'lavaan' output of a mediation model between Trust and Political Efficacy

```
Standardized Root Mean Square Residual:

  SRMR                                           0.044

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf =~
    actrolg           1.000                               1.412    0.593
    cptppol           1.025    0.044   23.523    0.000    1.448    0.595
    psppipl           1.340    0.066   20.428    0.000    1.892    0.858
    psppsgv           1.388    0.070   19.963    0.000    1.959    0.850
    ptcpplt           1.385    0.070   19.648    0.000    1.955    0.845
  Trust =~
    INSTT             1.000                               0.867    0.867
    IP                0.581    0.049   11.748    0.000    0.548    0.548
  INSTT =~
    trstlgl           1.000                               1.945    0.786
    trstplc           0.835    0.032   26.315    0.000    1.624    0.655
    trstplt           1.121    0.038   29.450    0.000    2.181    0.860
    trstep            0.629    0.039   16.033    0.000    1.223    0.503
    trstun            0.549    0.038   14.310    0.000    1.067    0.457
    trstprt           1.014    0.038   26.960    0.000    1.972    0.804
    trstprl           1.148    0.036   31.547    0.000    2.232    0.893
  IP =~
    ppltrst           1.000                               1.787    0.780
    pplfair           0.907    0.045   19.924    0.000    1.620    0.745
    pplhlp            0.888    0.047   19.022    0.000    1.587    0.690

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf ~
    agea      (c)    -0.008    0.002   -3.120    0.002   -0.005   -0.095
    edlvdhu  (c1)     0.034    0.016    2.152    0.031    0.024    0.066
    hinctnta (c2)    -0.040    0.019   -2.165    0.030   -0.028   -0.077
    gndr     (c3)    -0.172    0.080   -2.154    0.031   -0.122   -0.060
    fclcntr  (c4)     0.198    0.077    2.562    0.010    0.140    0.087
    lrscale  (c5)    -0.038    0.022   -1.740    0.082   -0.027   -0.061
  Trust ~
    agea      (a)     0.006    0.004    1.699    0.089    0.004    0.063
    edlvdhu  (a1)     0.061    0.022    2.780    0.005    0.036    0.100
    hinctnta (a2)     0.139    0.023    5.986    0.000    0.082    0.223
    gndr     (a3)     0.099    0.116    0.858    0.391    0.059    0.029
    fclcntr  (a4)    -0.674    0.096   -7.021    0.000   -0.400   -0.248
    lrscale  (a5)     0.258    0.027    9.589    0.000    0.153    0.349
  PolEf ~
    Trust     (b)     0.699    0.071    9.836    0.000    0.835    0.835
```

Figure A.33: The 'lavaan' output of a mediation model between Trust and Political Efficacy

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.actrolg ~~						
.cptppol	2.080	0.146	14.242	0.000	2.080	0.555
.trstplt ~~						
.trstprt	0.950	0.097	9.844	0.000	0.950	0.503
.trstep ~~						
.trstun	3.148	0.178	17.680	0.000	3.148	0.722
.trstlgl ~~						
.trstplc	0.993	0.112	8.895	0.000	0.993	0.346

Intercepts:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.actrolg	1.566	0.329	4.754	0.000	1.566	0.658
.cptppol	1.853	0.338	5.487	0.000	1.853	0.761
.psppipl	1.326	0.433	3.059	0.002	1.326	0.601
.psppsgv	1.469	0.450	3.266	0.001	1.469	0.638
.ptcpplt	1.419	0.449	3.160	0.002	1.419	0.613
.trstlgl	2.808	0.425	6.611	0.000	2.808	1.134
.trstplc	3.753	0.360	10.425	0.000	3.753	1.514
.trstplt	0.872	0.473	1.843	0.065	0.872	0.344
.trstep	3.846	0.282	13.643	0.000	3.846	1.582
.trstun	4.488	0.251	17.885	0.000	4.488	1.922
.trstprt	1.109	0.430	2.580	0.010	1.109	0.452
.trstprl	1.664	0.483	3.446	0.001	1.664	0.665
.ppltrst	3.073	0.260	11.823	0.000	3.073	1.340
.pplfair	3.578	0.236	15.127	0.000	3.578	1.644
.pplhlp	3.309	0.234	14.135	0.000	3.309	1.440
.PolEf	0.000				0.000	0.000
.Trust	0.000				0.000	0.000
.INSTT	0.000				0.000	0.000
.IP	0.000				0.000	0.000

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.actrolg	3.671	0.174	21.154	0.000	3.671	0.648
.cptppol	3.829	0.182	21.043	0.000	3.829	0.646
.psppipl	1.285	0.084	15.239	0.000	1.285	0.264
.psppsgv	1.470	0.092	16.022	0.000	1.470	0.277
.ptcpplt	1.533	0.096	15.921	0.000	1.533	0.286
.trstlgl	2.347	0.125	18.753	0.000	2.347	0.383
.trstplc	3.510	0.169	20.754	0.000	3.510	0.571
.trstplt	1.677	0.108	15.572	0.000	1.677	0.261
.trstep	4.412	0.205	21.546	0.000	4.412	0.747
.trstun	4.312	0.202	21.296	0.000	4.312	0.791
.trstprt	2.131	0.122	17.525	0.000	2.131	0.354
.trstprl	1.272	0.095	13.345	0.000	1.272	0.203
.ppltrst	2.060	0.156	13.242	0.000	2.060	0.392
.pplfair	2.110	0.140	15.036	0.000	2.110	0.446
.pplhlp	2.764	0.161	17.200	0.000	2.764	0.523
.PolEf	0.716	0.117	6.113	0.000	0.359	0.359
.Trust	2.083	0.239	8.707	0.000	0.733	0.733
.INSTT	0.939	0.193	4.863	0.000	0.248	0.248
.IP	2.236	0.193	11.587	0.000	0.700	0.700

Figure A.34: The 'lavaan' output of a mediation model between Trust and Political Efficacy

Defined Parameters:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ab_age	0.004	0.002	1.708	0.088	0.003	0.053
a1b_edl	0.042	0.016	2.667	0.008	0.030	0.084
a2b_inco	0.097	0.019	5.061	0.000	0.069	0.186
a3b_gndr	0.069	0.081	0.858	0.391	0.049	0.024
a4b_fclcntr	-0.471	0.081	-5.838	0.000	-0.334	-0.207
a5b_lrscale	0.180	0.023	7.722	0.000	0.128	0.292
total_age	-0.003	0.003	-1.248	0.212	-0.002	-0.042
total1_edl	0.076	0.017	4.399	0.000	0.054	0.150
total2_inco	0.057	0.018	3.196	0.001	0.040	0.109
total3_gndr	-0.102	0.090	-1.137	0.255	-0.073	-0.036
total4_fclcntr	-0.273	0.074	-3.674	0.000	-0.193	-0.120
total5_lrscale	0.142	0.021	6.918	0.000	0.101	0.230

Figure A.35: The 'lavaan' output of a mediation model between Trust and Political Efficacy

b.4 Measurement Equivalence

```
Group 1 [Female]:

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf =~
    actrolg           1.000                               1.379    0.590
    cptppol (.p2.)    1.071    0.036   29.663    0.000    1.478    0.619
    psppipl (.p3.)    1.506    0.063   23.869    0.000    2.077    0.956
    psppsgv (.p4.)    1.332    0.056   24.003    0.000    1.837    0.780
    ptcpplt (.p5.)    1.292    0.055   23.700    0.000    1.782    0.773

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .actrolg ~~
   .cptppol           1.879    0.143   13.156    0.000    1.879    0.531
 .psppsgv ~~
   .ptcpplt           0.759    0.111    6.852    0.000    0.759    0.352

Intercepts:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .actrolg (.14.)    2.141    0.066   32.530    0.000    2.141    0.916
   .cptppol (.15.)    2.454    0.069   35.727    0.000    2.454    1.028
   .psppipl (.16.)    2.077    0.070   29.750    0.000    2.077    0.956
   .psppsgv (.17.)    2.265    0.070   32.373    0.000    2.265    0.961
   .ptcpplt (.18.)    2.213    0.069   32.251    0.000    2.213    0.960
    PolEf             0.000                               0.000    0.000

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .actrolg           3.565    0.174   20.456    0.000    3.565    0.652
   .cptppol           3.519    0.174   20.223    0.000    3.519    0.617
   .psppipl           0.402    0.110    3.665    0.000    0.402    0.085
   .psppsgv           2.180    0.136   16.031    0.000    2.180    0.392
   .ptcpplt           2.141    0.128   16.686    0.000    2.141    0.403
    PolEf             1.902    0.167   11.399    0.000    1.000    1.000
```

Figure A.36: The 'lavaan' output of the scalar equivalent model

```
Group 2 [Male]:

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PolEf =~
    actrolg           1.000                               1.358    0.555
    cptppol (.p2.)    1.071    0.036   29.663    0.000    1.455    0.565
    psppipl (.p3.)    1.506    0.063   23.869    0.000    2.045    0.925
    psppsgv (.p4.)    1.332    0.056   24.003    0.000    1.809    0.811
    ptcpplt (.p5.)    1.292    0.055   23.700    0.000    1.754    0.781

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .actrolg ~~
   .cptppol           2.570    0.202   12.723    0.000    2.570    0.595
 .psppsgv ~~
   .ptcpplt           0.302    0.118    2.567    0.010    0.302    0.165

Intercepts:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .actrolg (.14.)    2.141    0.066   32.530    0.000    2.141    0.876
   .cptppol (.15.)    2.454    0.069   35.727    0.000    2.454    0.953
   .psppipl (.16.)    2.077    0.070   29.750    0.000    2.077    0.940
   .psppsgv (.17.)    2.265    0.070   32.373    0.000    2.265    1.016
   .ptcpplt (.18.)    2.213    0.069   32.251    0.000    2.213    0.986
    PolEf             0.145    0.071    2.049    0.040    0.107    0.107

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .actrolg           4.133    0.233   17.733    0.000    4.133    0.692
   .cptppol           4.515    0.254   17.781    0.000    4.515    0.681
   .psppipl           0.701    0.127    5.532    0.000    0.701    0.144
   .psppsgv           1.698    0.140   12.140    0.000    1.698    0.342
   .ptcpplt           1.966    0.147   13.412    0.000    1.966    0.390
    PolEf             1.843    0.173   10.642    0.000    1.000    1.000
```

Figure A.37: The 'lavaan' output of the scalar equivalent model

c Tables

Model Equations

Latent Factor	**SEM Equation**
PolEf	$\text{PolEf} = \theta_1 \cdot \text{actrolg} + \theta_2 \cdot \text{cptppol} + \theta_3 \cdot \text{psppipl} + \theta_4 \cdot \text{psppsgv} + \theta_5 \cdot \text{ptcpplt} + \varepsilon_1$ actrolg $\sim\sim$ cptppol psppsgv $\sim\sim$ ptcpplt
SatCSA	$\text{SatCSA} = \theta_1 \cdot \text{stfeco} + \theta_2 \cdot \text{stfgov} + \theta_3 \cdot \text{stfdem} + \theta_4 \cdot \text{stfedu} + \theta_5 \cdot \text{stfhlth} + \varepsilon_1$ stfedu $\sim\sim$ stfhlth stfeco $\sim\sim$ stfgov
IP	$\text{IP} = \theta_1 \cdot \text{ppltrst} + \theta_2 \cdot \text{pplfair} + \theta_3 \cdot \text{pplhlp} + \varepsilon_1$
INSTT	$\text{INSTT} = \theta_1 \cdot \text{trstlgl} + \theta_2 \cdot \text{trstplc} + \theta_3 \cdot \text{trstplt} + \theta_4 \cdot \text{trstep} + \theta_5 \cdot \text{trstun} + \theta_6 \cdot \text{trstprt} + \theta_7 \cdot \text{trstprl} + \varepsilon_1$ trstplt $\sim\sim$ trstprt trstep $\sim\sim$ trstun trstlgl $\sim\sim$ trstplc

Table A.2: Equations of latent factors in the single-factor models

Fit indices and χ^2 test results relating to the measurement model

	fit_cfa_PolEf	fit_cfa_PolEf2	fit_cfa_PolEf3
logl	-16686.66	-16398.70	-16379.21
χ^2	631.64	55.72	16.73
df	5.00	4.00	3.00
pvalue	0.00	0.00	0.00
cfi	0.87	0.99	1.00
tli	0.74	0.97	0.99
rmsea	0.27	0.09	0.05

Table A.3: Fit indices for PolEf models

	Df	AIC	BIC	χ^2	χ^2 diff	RMSEA	$\Pr(>\chi^2)$
fit_cfa_PolEf vs fit_cfa_PolEf2							
fit_cfa_PolEf2	4	32829	32916	55.72			
fit_cfa_PolEf	5	33403	33485	631.64	575.92	0.58343	$< 2.2 \times 10^{-16}$
fit_cfa_PolEf2 vs fit_cfa_PolEf3							
fit_cfa_PolEf3	3	32792	32885	16.733			
fit_cfa_PolEf2	4	32829	32916	55.720	38.987	0.14997	4.267×10^{-10}

Table A.4: χ^2 Difference Tests for PolEf

	fit_cfa_SatCSA	fit_cfa_SatCSA2	fit_cfa_SatCSA3
logl	-16125.83	-16033.46	-16024.98
χ^2	207.68	22.95	5.99
df	5.00	4.00	3.00
pvalue	0.00	0.00	0.11
cfi	0.96	1.00	1.00
tli	0.92	0.99	1.00
rmsea	0.15	0.05	0.02

Table A.5: Fit indices for SatCSA models

	Df	AIC	BIC	χ^2	χ^2 diff	RMSEA	Pr($>\chi^2$)
fit_cfa_SatCSA vs fit_cfa_SatCSA2							
fit_cfa_SatCSA2	4	32099	32186	22.952			
fit_cfa_SatCSA	5	32282	32363	207.679	184.73	0.32972	$< 2.2 \times 10^{-16}$
fit_cfa_SatCSA2 vs fit_cfa_SatCSA3							
fit_cfa_SatCSA3	3	32084	32176	5.9867			
fit_cfa_SatCSA2	4	32099	32186	22.952	16.965	0.097195	0.00003807

Table A.6: χ^2 Difference Tests for SatCSA

	fit_cfa_INSTT	fit_cfa_INSTT2	fit_cfa_INSTT3	fit_cfa_INSTT4
logl	-23472.58	-23153.06	-22636.99	-22567.47
χ^2	1947.16	1308.13	275.97	136.94
df	14.00	13.00	12.00	11.00
pvalue	0.00	0.00	0.00	0.00
cfi	0.76	0.84	0.97	0.98
tli	0.65	0.75	0.94	0.97
rmsea	0.29	0.24	0.11	0.08

Table A.7: Fit indices for INSTT models

	Df	AIC	BIC	χ^2	χ^2 diff	RMSEA	Pr($>\chi^2$)
fit_cfa_INSTT vs fit_cfa_INSTT2							
fit_cfa_INSTT2	13	46350	46470	1308.1			
fit_cfa_INSTT	14	46987	47101	1947.2	639.03	0.6148	$< 2.2 \times 10^{-16}$
fit_cfa_INSTT2 vs fit_cfa_INSTT3							
fit_cfa_INSTT3	12	45320	45445	275.97			
fit_cfa_INSTT2	13	46350	46470	1308.13	1032.2	0.78158	$< 2.2 \times 10^{-16}$
fit_cfa_INSTT3 vs fit_cfa_INSTT4							
fit_cfa_INSTT4	11	45183	45313	136.94			
fit_cfa_INSTT3	12	45320	45445	275.97	139.03	0.28596	$< 2.2 \times 10^{-16}$

Table A.8: χ^2 Difference Tests for INSTT

	fit_cfa_Trust	fit_cfa_Trust2	fit_cfa_Trust3	fit_cfa_Trust4
logl	-34102.94	-33784.08	-33267.12	-33197.79
χ^2	1978.80	1341.07	307.16	168.50
df	34.00	33.00	32.00	31.00
pvalue	0.00	0.00	0.00	0.00
cfi	0.80	0.87	0.97	0.99
tli	0.74	0.82	0.96	0.98
rmsea	0.18	0.15	0.07	0.05

Table A.9: Fit indices for Trust models

	Df	AIC	BIC	χ^2	χ^2 diff	RMSEA	$\Pr(> \chi^2)$
fit_cfa_Trust vs fit_cfa_Trust2							
fit_cfa_Trust2	33	67632	67806	1341.1			
fit_cfa_Trust	34	68268	68436	1978.8	637.73	0.61363	$< 2.2 \times 10^{-16}$
fit_cfa_Trust2 vs fit_cfa_Trust3							
fit_cfa_Trust3	32	66600	66780	307.16			
fit_cfa_Trust2	33	67632	67806	1341.07	1033.9	0.78156	$< 2.2 \times 10^{-16}$
fit_cfa_Trust3 vs fit_cfa_Trust4							
fit_cfa_Trust4	31	66464	66648	168.50			
fit_cfa_Trust3	32	66600	66780	307.16	138.66	0.28532	$< 2.2 \times 10^{-16}$

Table A.10: χ^2 tests for Trust models

	fit_cfa_POL
logl	-64527.553
aic	129195.106
bic	129575.422
χ^2	901.400
df	160.000
pvalue	0.000
cfi	0.966
tli	0.960
rmsea	0.052

Table A.11: Fit measures of the complete measurement model

	w.lrscale	w.hinctnta	w.hinctnta.1	w.hinctnta...fclcntr	w.hinctnta...agea	w.hinctnta...agea...gndr	w.hinctnta...agea...eduhl
logl	-54041.20	-54041.20	-46021.27	-45951.06	-46011.56	-46009.04	-45972.83
aic	108230.40	108230.40	92184.54	92046.11	92167.12	92164.08	92091.67
bic	108618.95	108618.95	92546.17	92412.72	92533.85	92535.90	92463.43
χ^2	1071.19	1071.19	922.22	1006.77	987.07	1021.69	1069.90
df	176.00	176.00	179.00	198.00	198.00	217.00	217.00
pvalue	0.00	0.00	0.00	0.00	0.00	0.00	0.00
cfi	0.95	0.95	0.95	0.95	0.95	0.95	0.95
tli	0.94	0.94	0.95	0.94	0.94	0.94	0.94
rmsea	0.06	0.06	0.06	0.06	0.06	0.06	0.06

Table A.12: Global fit indices of the MIMIC models.

Fit indices relating to mediation models

Table A.13: Fit Indices for Mediation Models

	Mediation_Trust	Mediation_SatCSA
LogL	-30169.307	-19616.718
AIC	60466.613	39323.436
BIC	60782.911	39545.833
χ^2	660.878	407.543
Degrees of Freedom	161	80
p-value	0.000	0.000
CFI	0.950	0.954
TLI	0.940	0.940
RMSEA	0.055	0.063

Fit indices and χ^2 test results relating to measurement equivalence models

Table A.14: χ^2 difference tests of measurement equivalence models

Models	Df	AIC	BIC	χ^2	χ^2 diff	RMSEA	Df diff	Pr(> χ^2)
fit_configural	6	32755	32940	18.711				
fit_metric	10	32750	32913	21.441	2.730	0.000000	4	0.6040074
fit_scalar	14	32779	32920	58.412	36.972	0.098796	4	0.0000001826***
fit_strict	19	32792	32906	81.532	23.120	0.065508	5	0.0003202***
fit_structural	20	32790	32899	81.533	0.001	0.000000	1	0.9781052

Table A.15: Fit measures of the measurement equivalence models.

	df	cfi	tli	rmsea	rmsea.ci.lower	rmsea.ci.upper	rmsea.pvalue	srmr
Configural	6	1.00	0.99	0.05	0.03	0.08	0.45	0.01
Metric	10	1.00	1.00	0.04	0.01	0.06	0.83	0.01
Scalar	14	0.99	0.99	0.06	0.05	0.08	0.11	0.03
Strict	19	0.99	0.99	0.06	0.05	0.08	0.07	0.04
Structural	20	0.99	0.99	0.06	0.05	0.07	0.10	0.04

Fit indices and χ^2 test results relating to partial scalar invariance

Table A.16: Partial scalar invariance model fit indices

Model	Df	CFI	TLI	RMSEA	RMSEA CI Lower	RMSEA CI Upper	RMSEA P-value	SRMR
Metric	10	1.00	1.00	0.04	0.01	0.06	0.83	0.01
Scalar	14	0.99	0.99	0.06	0.05	0.08	0.11	0.03
Plus_psppsgv	13	0.99	0.99	0.06	0.04	0.07	0.26	0.03
Plus_ptcpplt	12	1.00	0.99	0.05	0.03	0.07	0.59	0.02
Plus_psppipl	11	1.00	1.00	0.03	0.01	0.05	0.89	0.01

Table A.17: χ^2 difference tests of partial scalar invariance models

Models	Df	AIC	BIC	χ^2	χ^2 diff	RMSEA	Df diff	Pr(> χ^2)
fit_configural	6	32755	32940	18.711				
fit_metric	10	32750	32913	21.441	2.730	0.000000	4	0.604007
fit_scalar	14	32779	32920	58.412	36.972	0.098796	4	0.0000001826***
fit_scalar_psppsgv	13	32770	32917	47.439	25.998	0.095276	3	0.0000095462***
fit_scalar_psppsgv_ptcpplt	12	32758	32911	33.793	12.353	0.078290	2	0.002078**
fit_scalar_psppsgv_ptcpplt_psppipl	11	32748	32906	21.474	0.034	0.000000	1	0.854337

Multi-group SEM

Table A.18: χ^2 difference test, MG-SEM

Models	Df	AIC	BIC	χ^2	χ^2 diff	RMSEA	Df diff	Pr(> χ^2)
Unconstrained	88	45817	46133	322.52				
Constraineds	91	45815	46115	326.17	3.6472	0.01893	3	0.3022

Table A.19: Fit indices, MG-SEM

Model	Df	CFI	TLI	RMSEA	RMSEA CI Lower	RMSEA CI Upper	RMSEA P-value	SRMR
Unconstrained	88	0.97	0.96	0.07	0.06	0.07	0	0.05
Constrained	91	0.97	0.96	0.07	0.06	0.07	0	0.05

d Figures

Missing Data Pattern

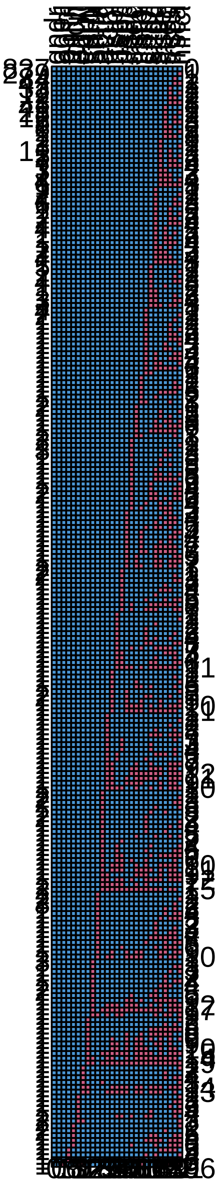

Figure A.38: Missing data pattern.

Checking linearity assumptions

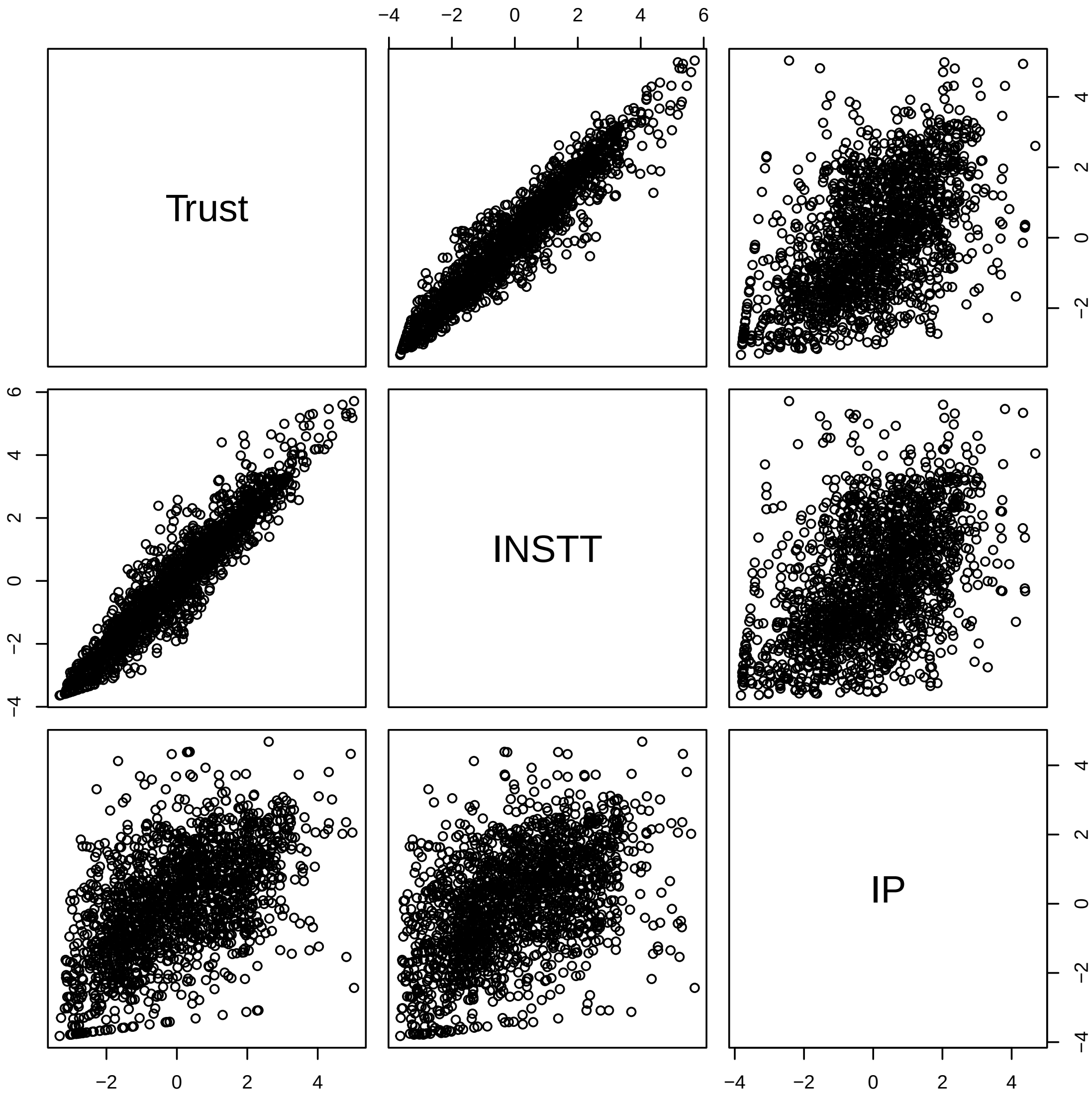

Figure A.39: Pairs panels: Checking linearity assumptions among Trust and its indicator factors, Institutional trust and Interpersonal trust.

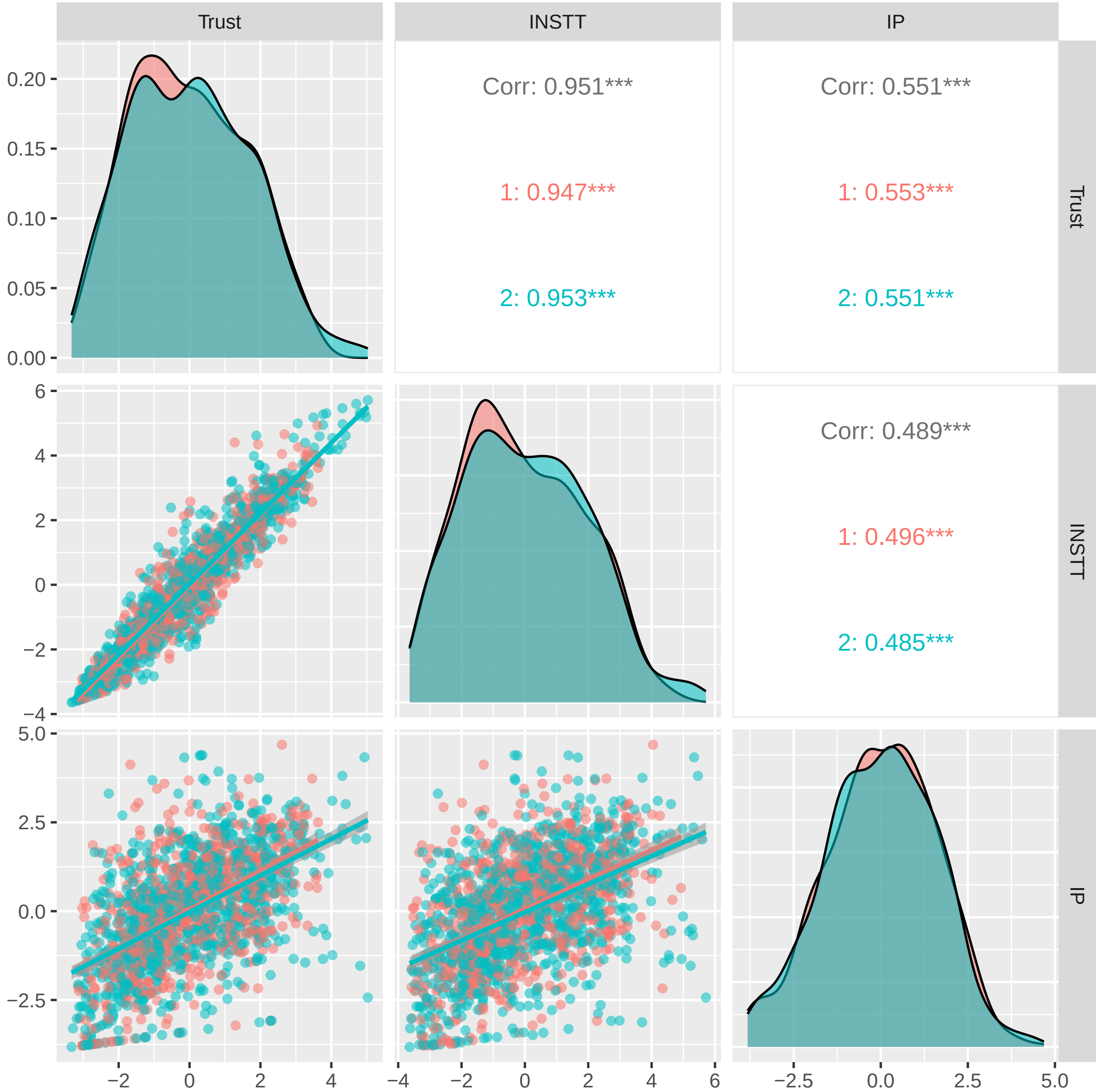

Figure A.40: GGplot pairs panel: Checking linearity assumptions among Trust and its indicator factors, Institutional trust and Interpersonal trust per gender.

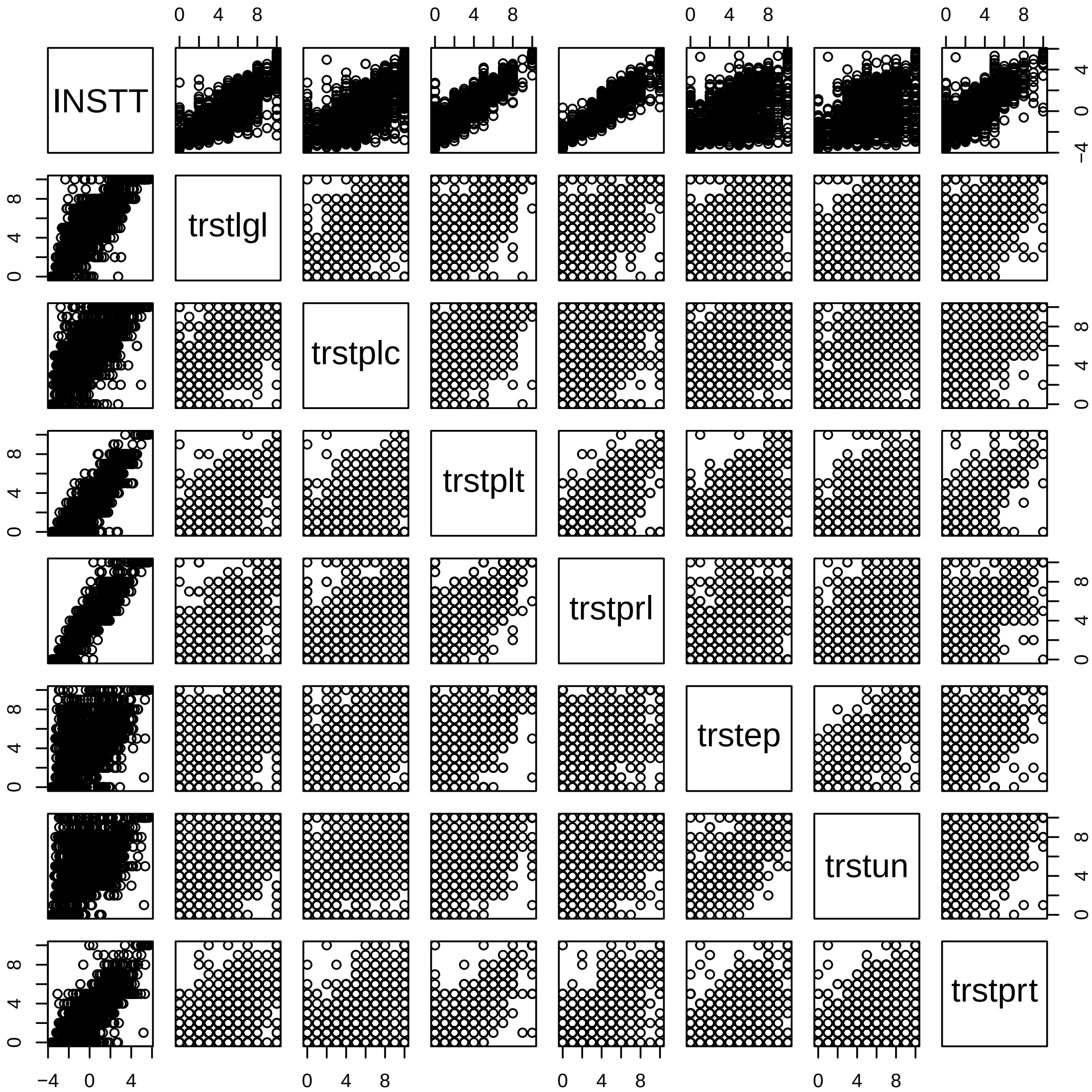

Figure A.41: Pairs panel: Checking linearity assumptions among Institutional trust and its indicator variables.

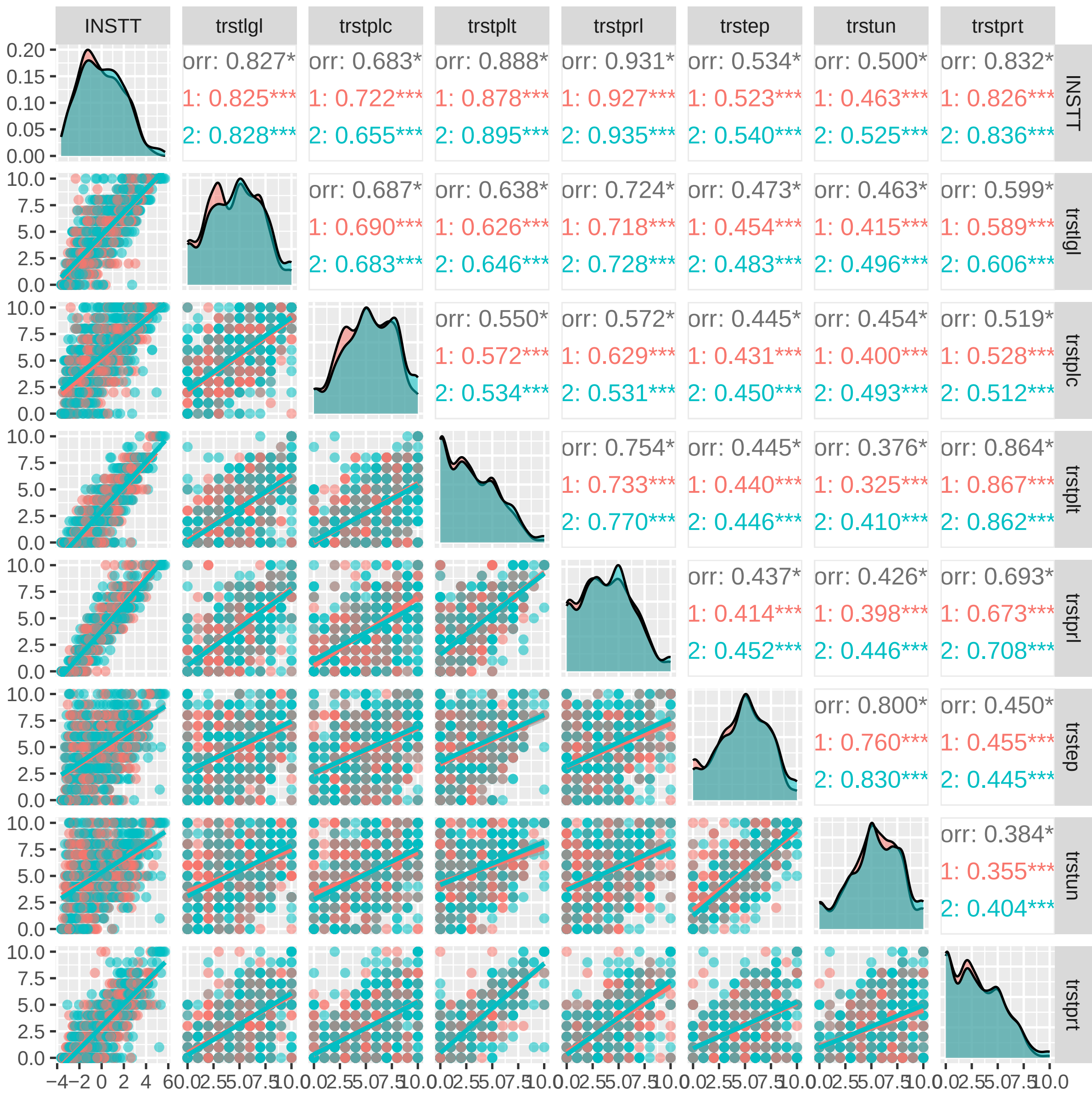

Figure A.42: GGplot pairs panel: Checking linearity assumptions among Institutional trust and its indicator variables per gender.

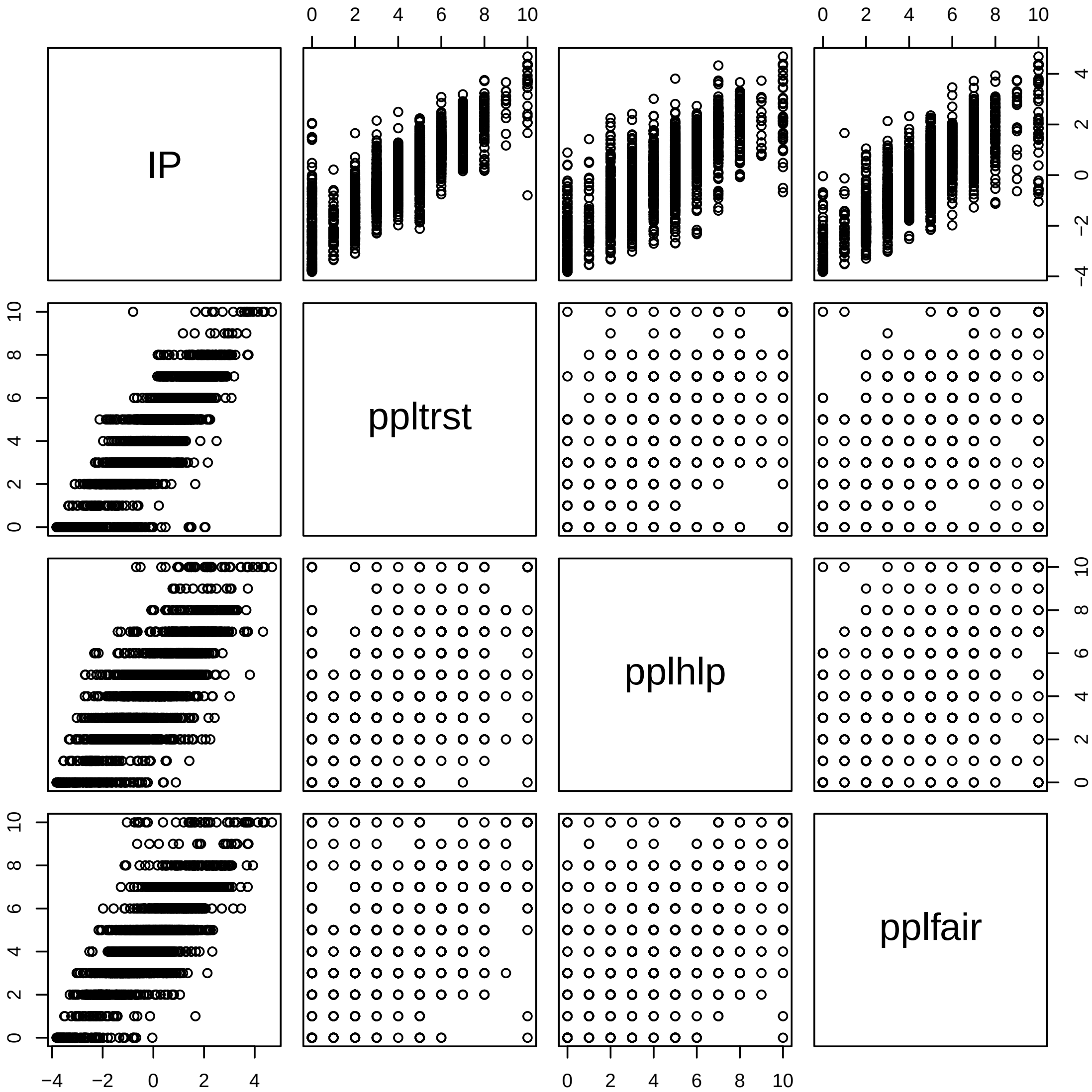

Figure A.43: Pairs panel: Checking linearity assumptions among Interpersonal trust and its indicator variables.

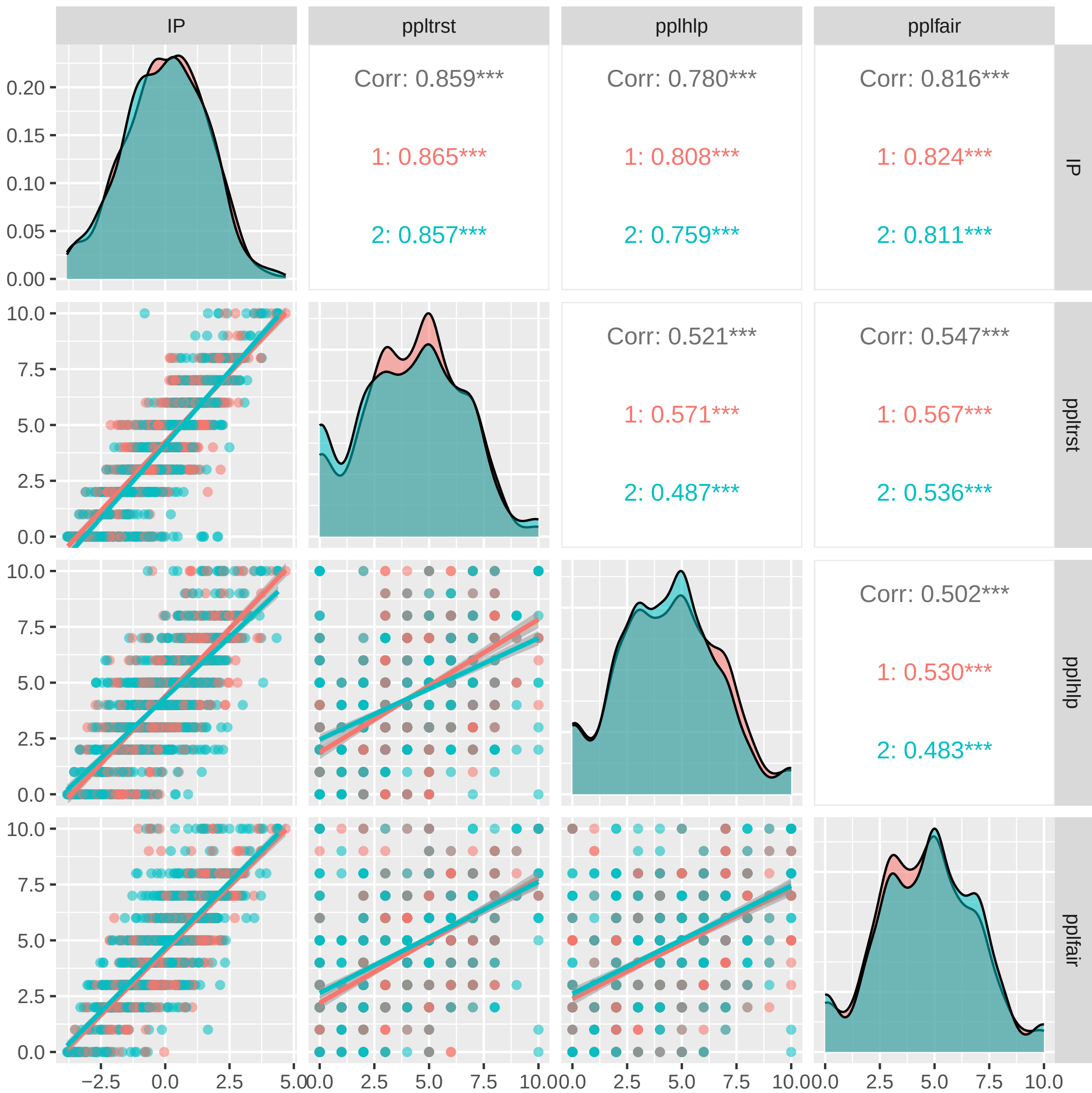

Figure A.44: GGplot pairs panel: Checking linearity assumptions among Interpersonal trust and its indicator variables per gender.

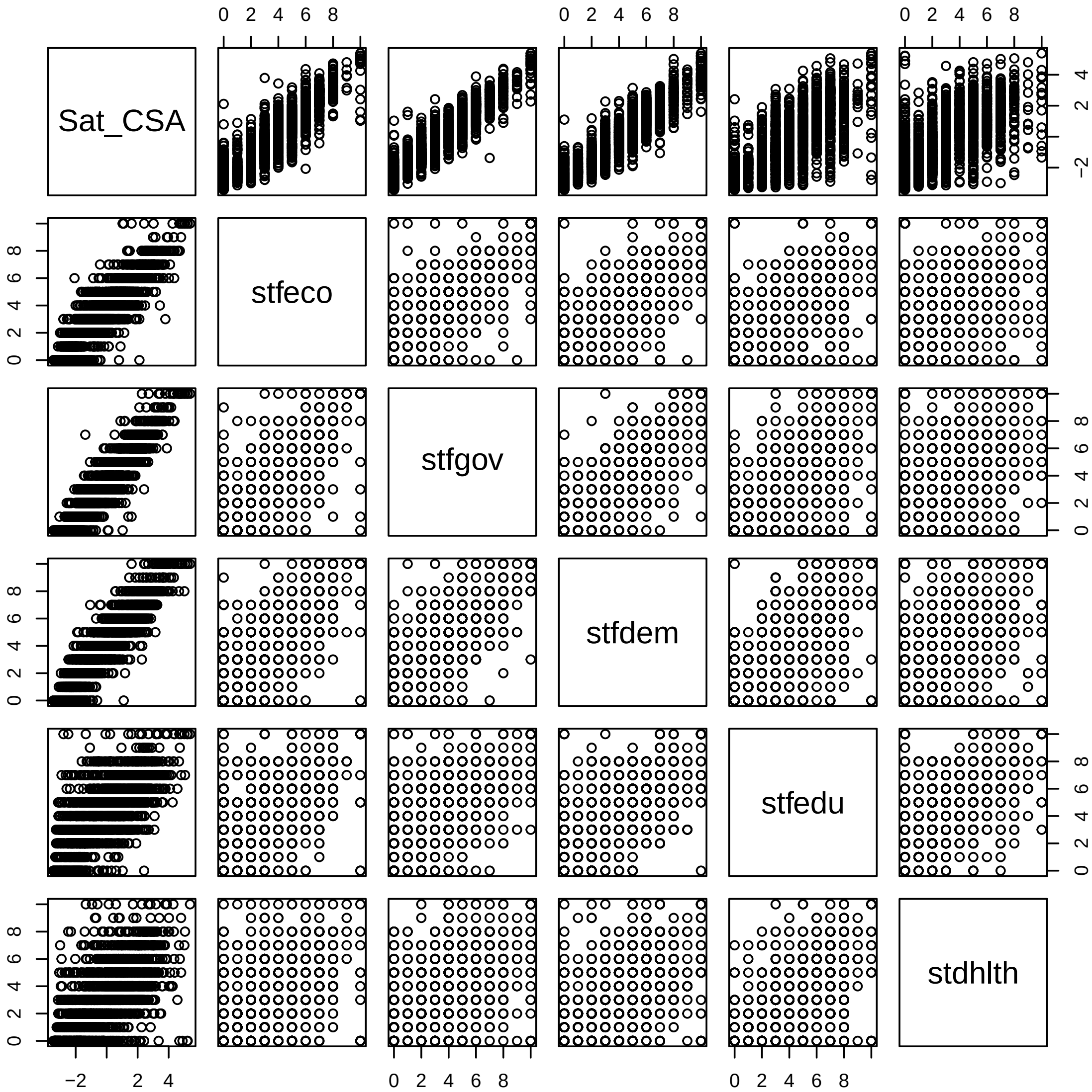

Figure A.45: Pairs panel: Checking linearity assumptions among Satisfaction with the current state of affairs and its indicator variables.

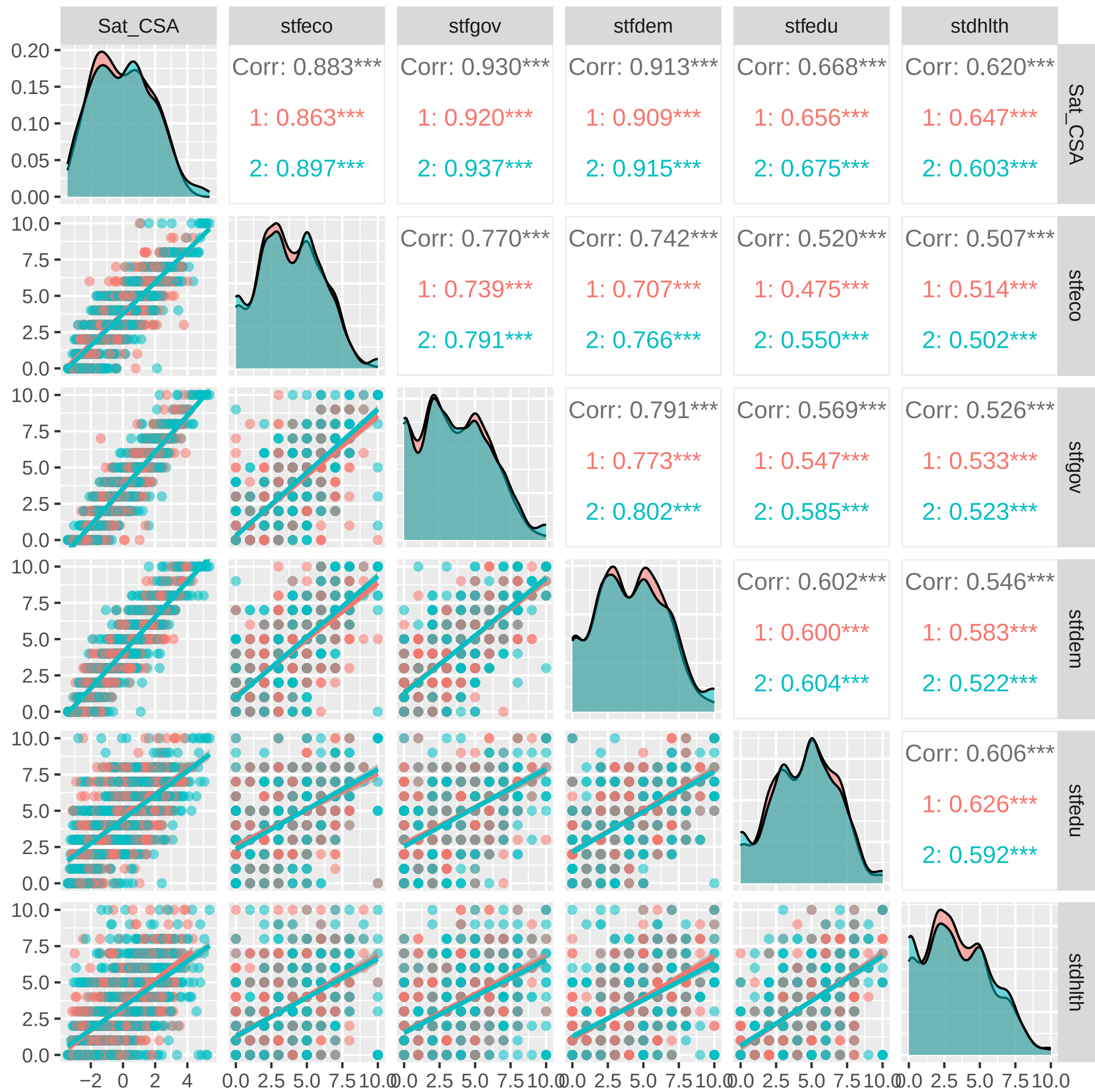

Figure A.46: GGplot pairs panel: Checking linearity assumptions among Satisfaction with the current state of affairs and its indicator variables per gender.

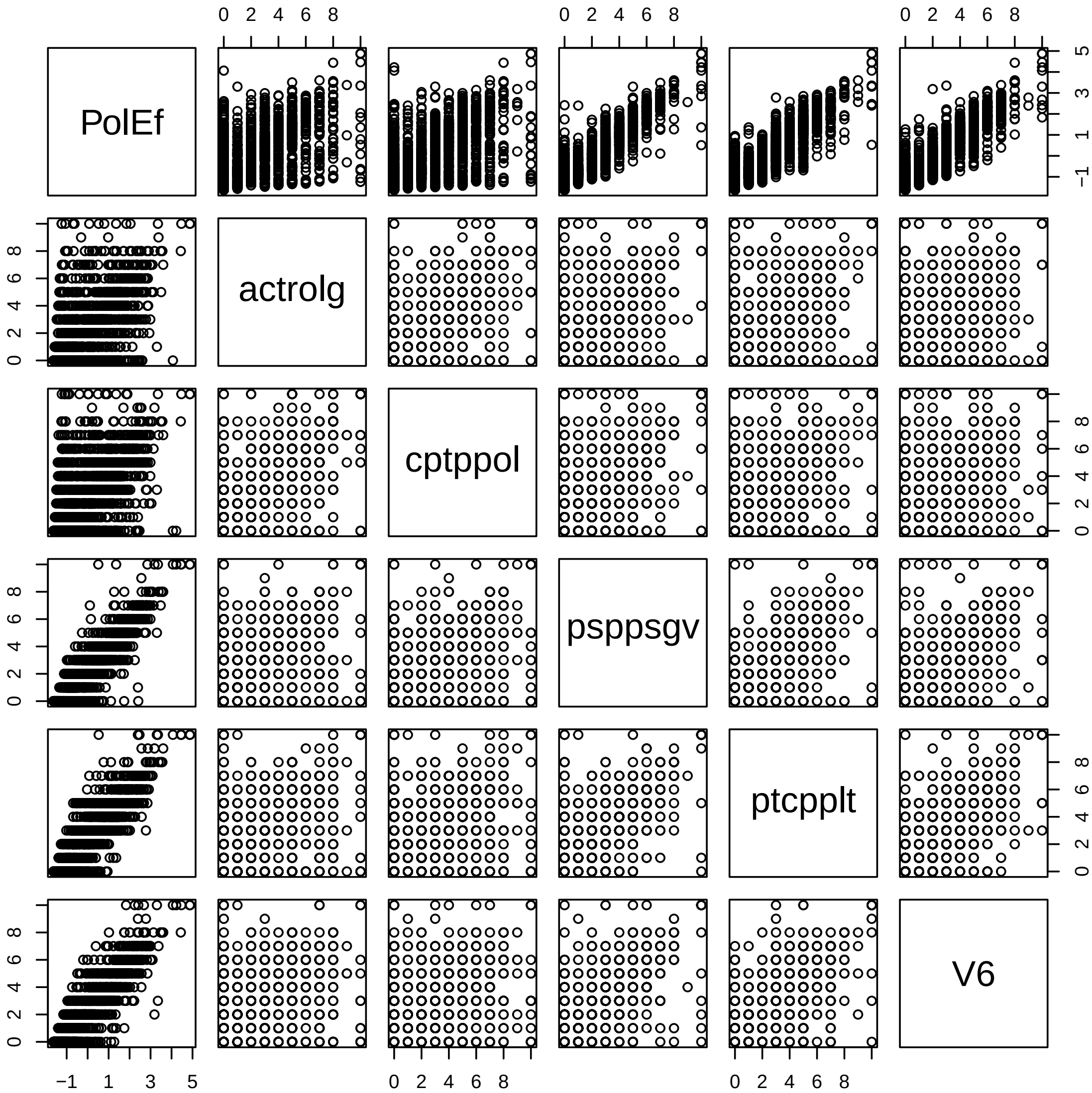

Figure A.47: Pairs panel: Checking linearity assumptions among Political Efficacy and its indicator variables.

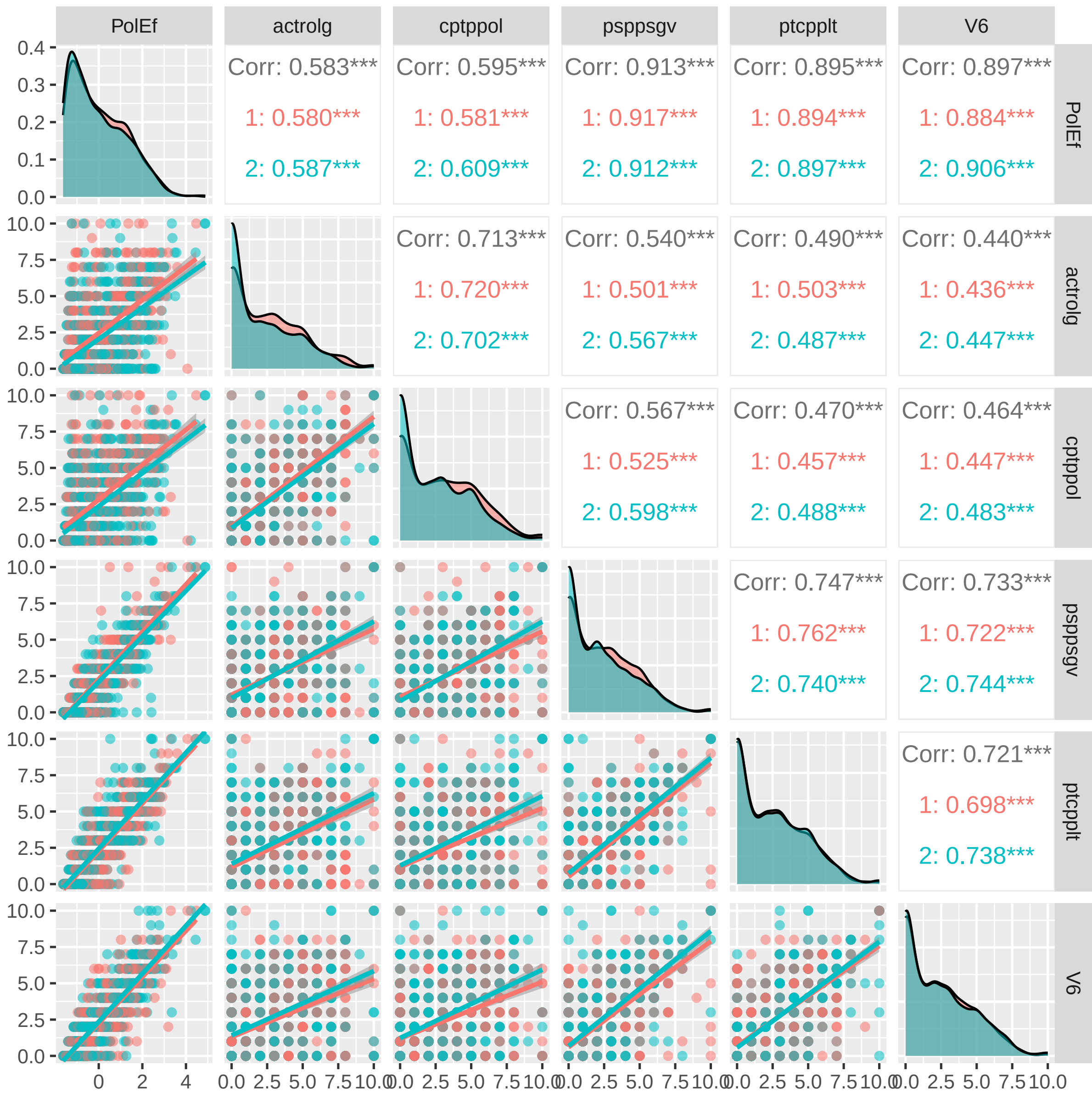

Figure A.48: GGplot pairs panel: Checking linearity assumptions among Political Efficacy and its indicator variables per gender.

Observed correlations among the indicator variables

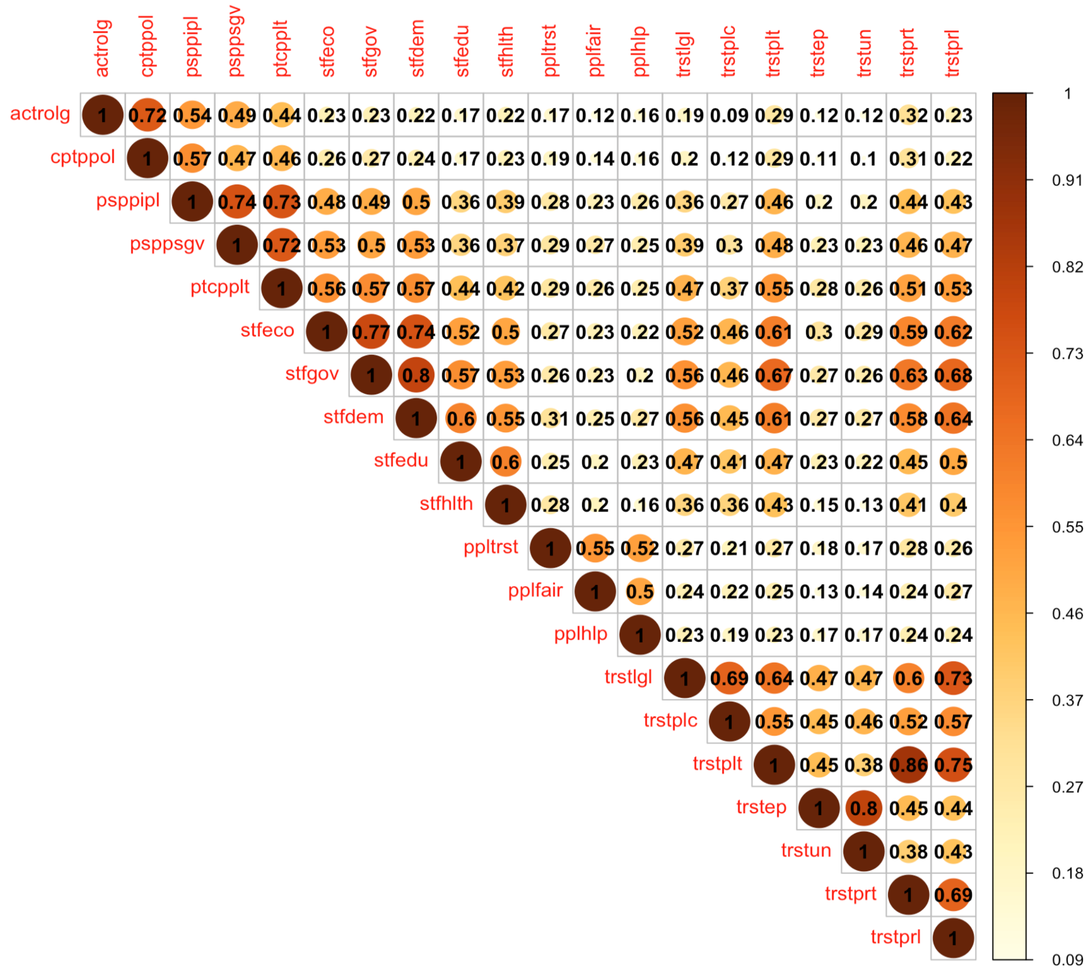

Figure A.49: Observed correlations among the indicator variables.

Histograms

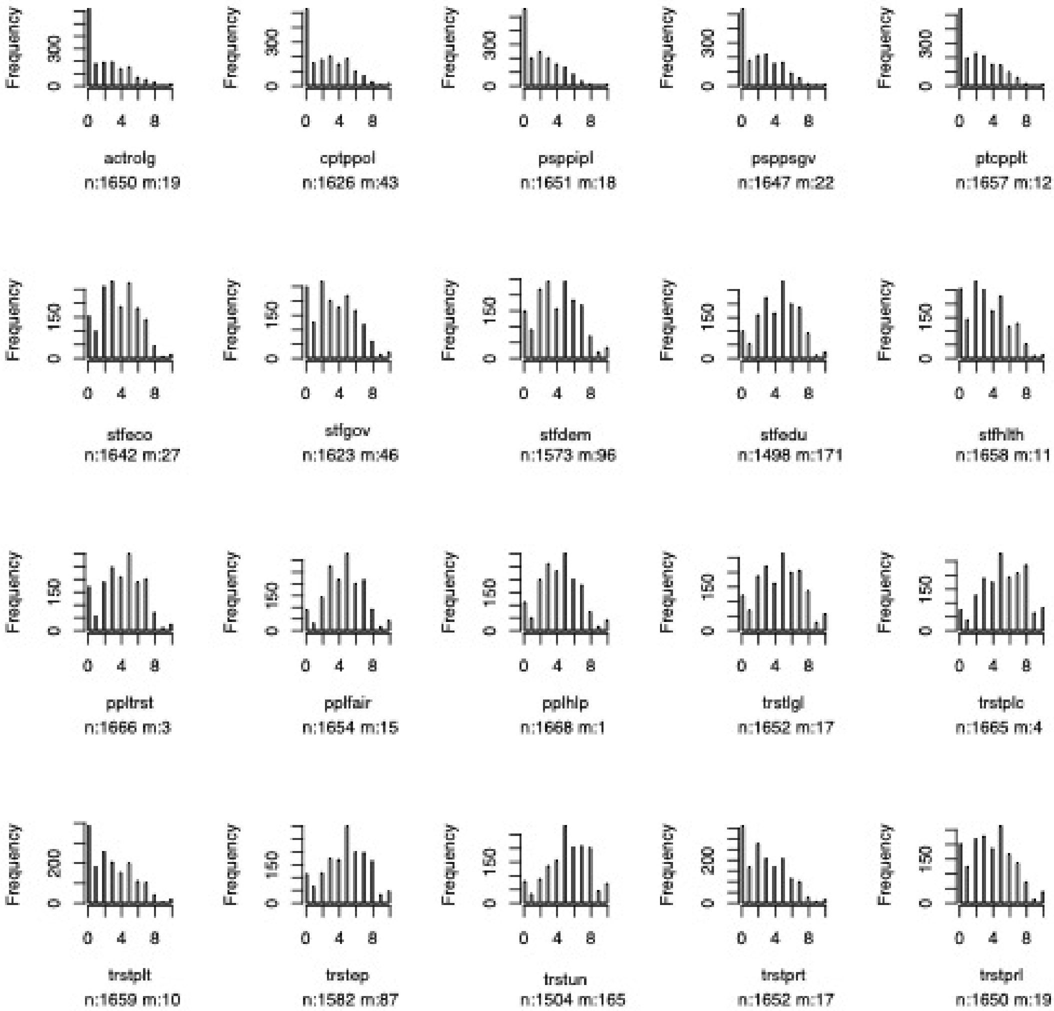

Figure A.50: histograms

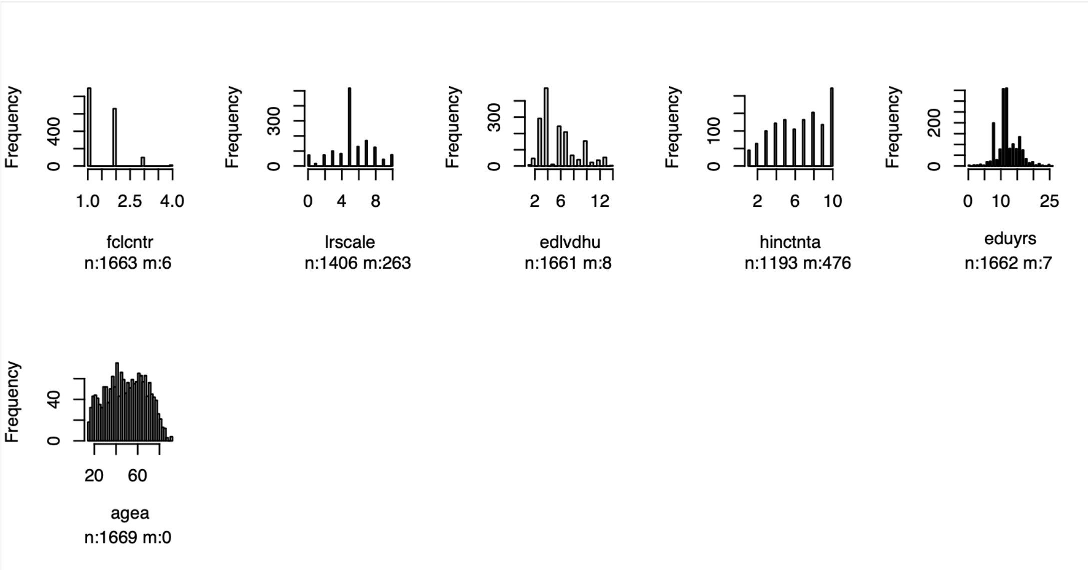

Figure A.51: histograms

Measurement model path plot

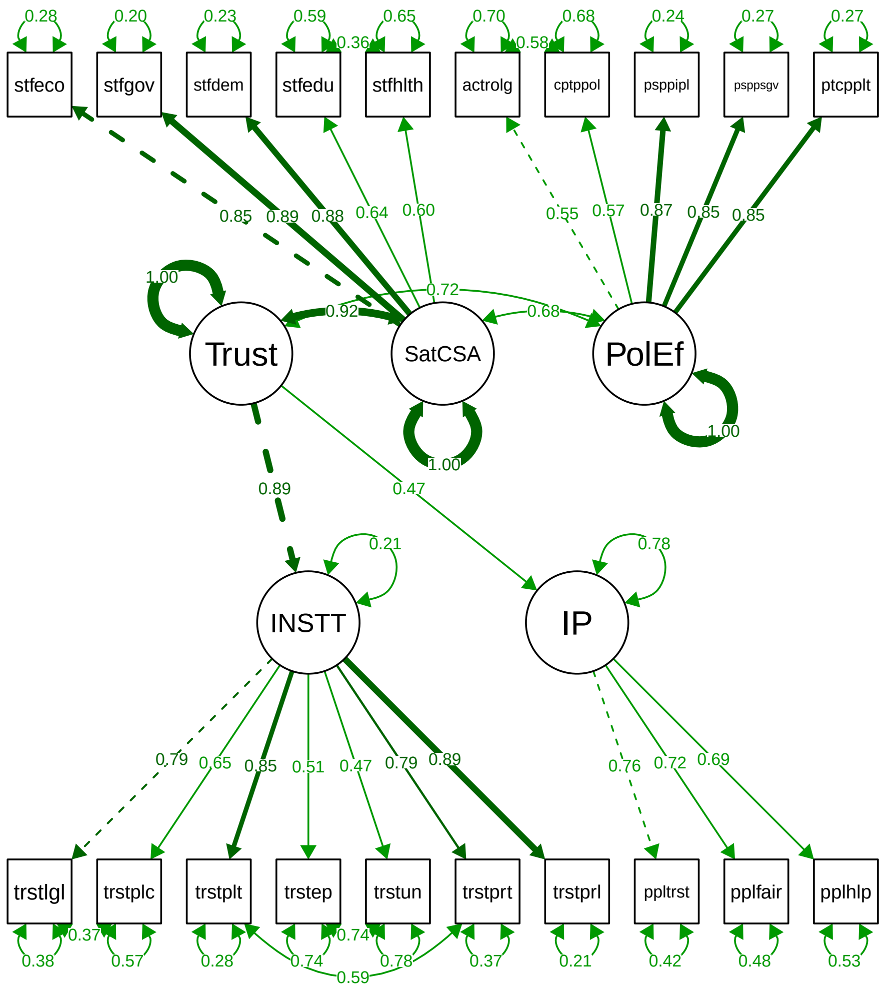

Figure A.52: The complete measurement model.

MIMIC model path plots

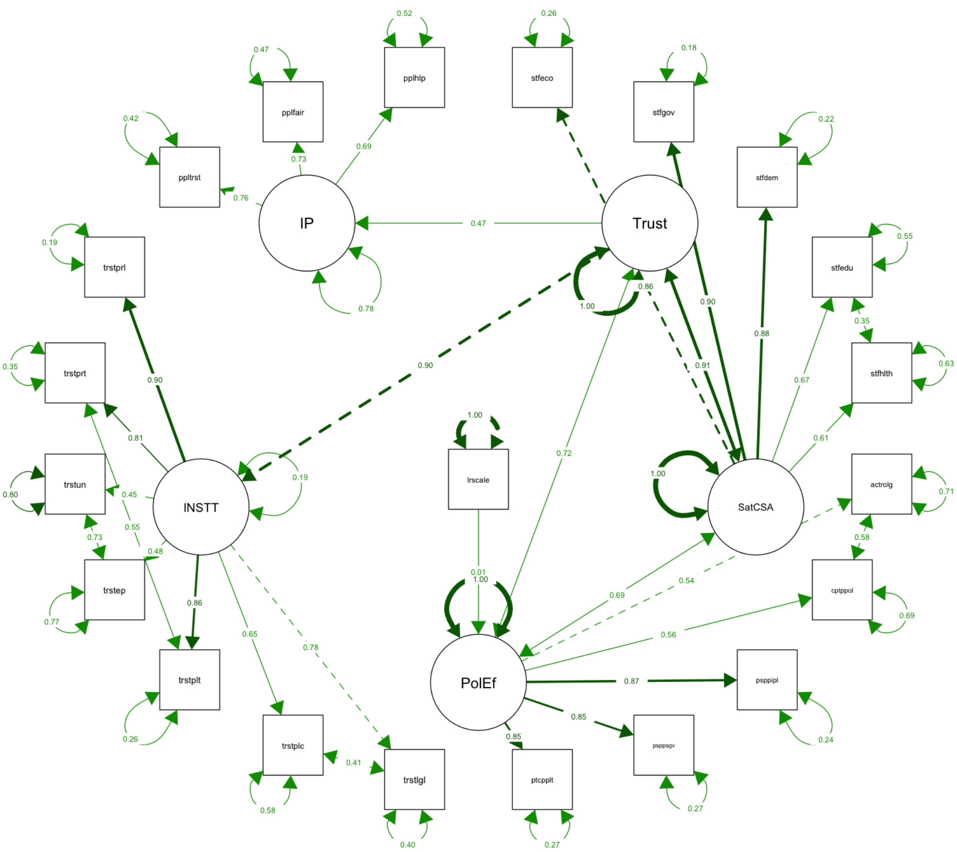

Figure A.53: The MIMIC model, where latent variable Political Efficacy was regressed on Political Orientation.

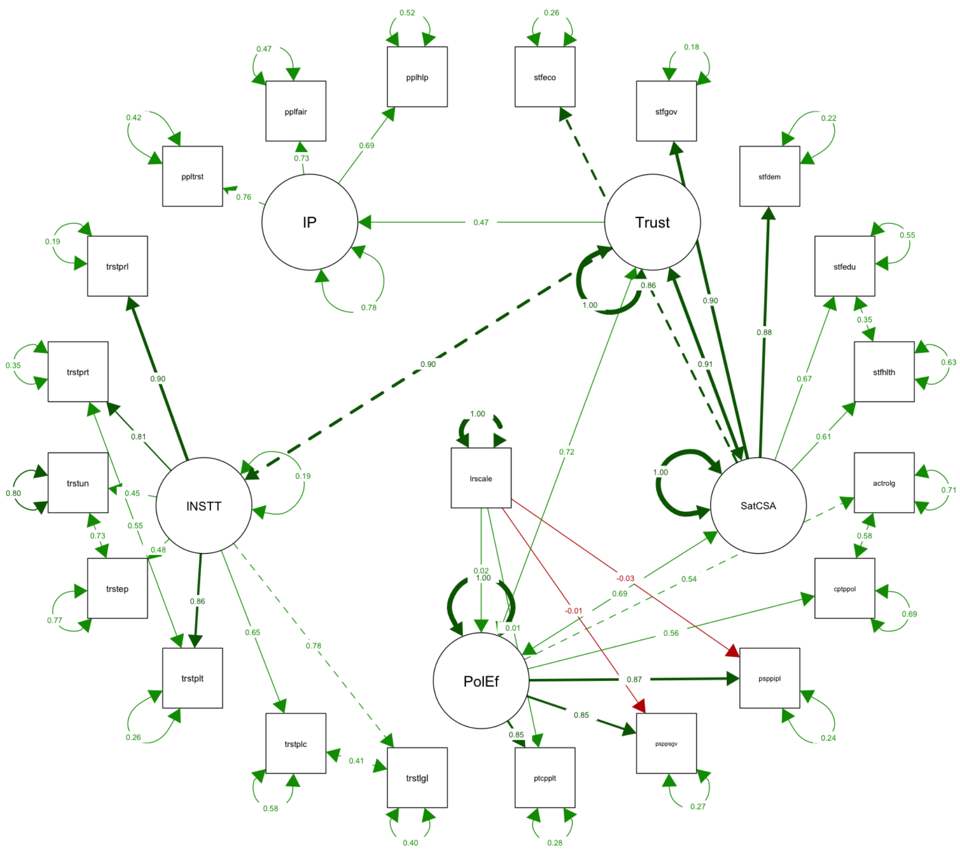

Figure A.54: The MIMIC model, where latent variable Political Efficacy and its External Political Efficacy related indicators were regressed on Political Orientation.

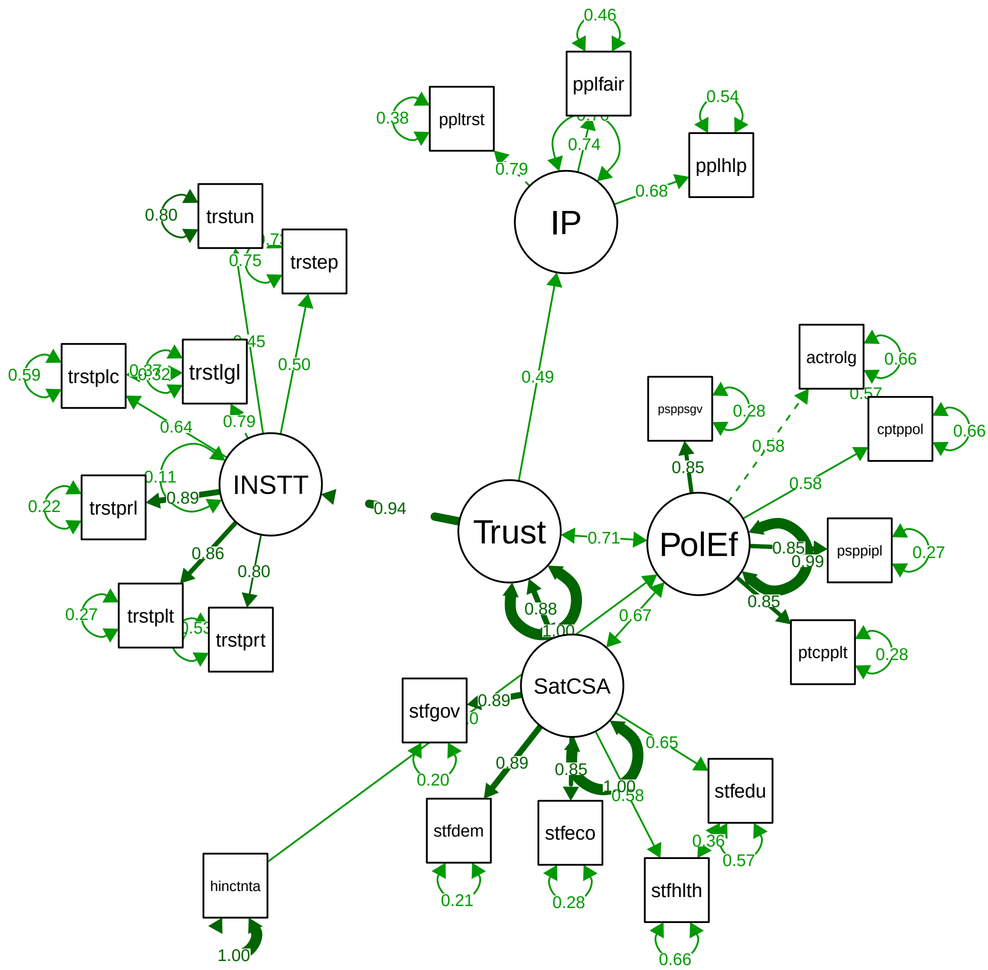

Figure A.55: The MIMIC model, where latent variable Political Efficacy was regressed on Income.

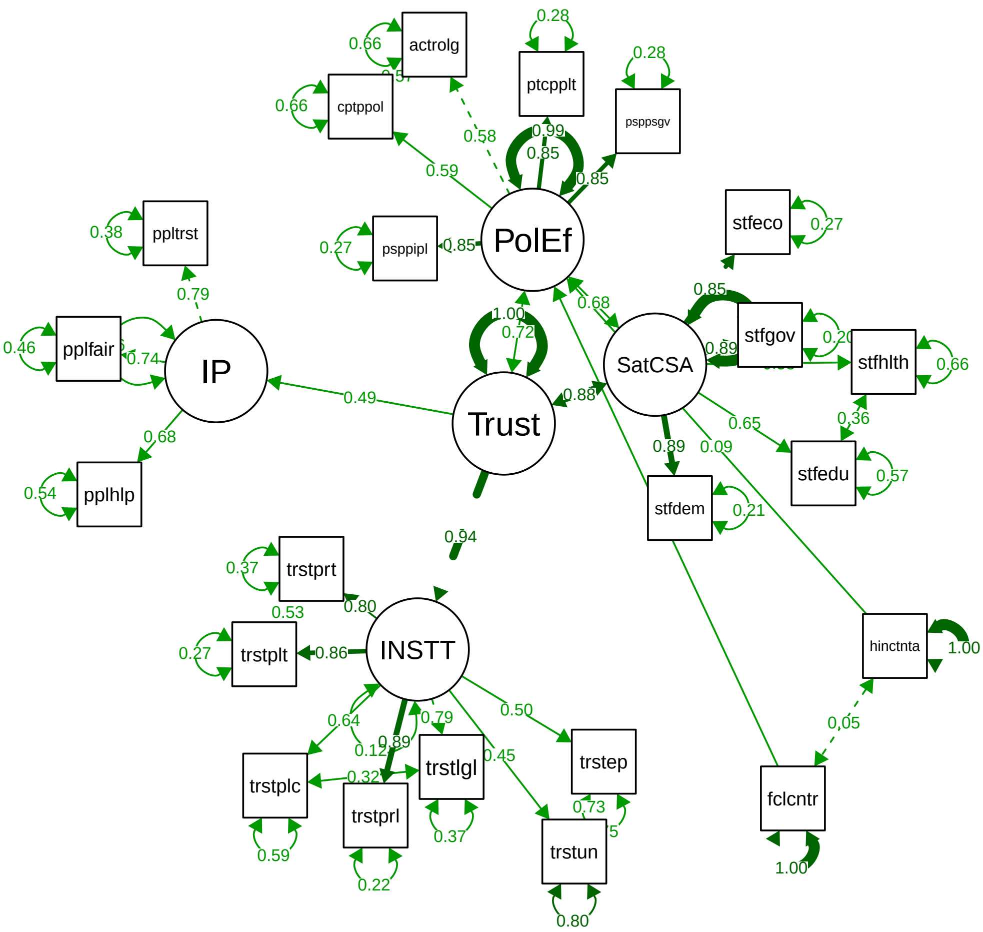

Figure A.56: The MIMIC model, where latent variable Political Efficacy was regressed on Income and Feeling Close to One's Country

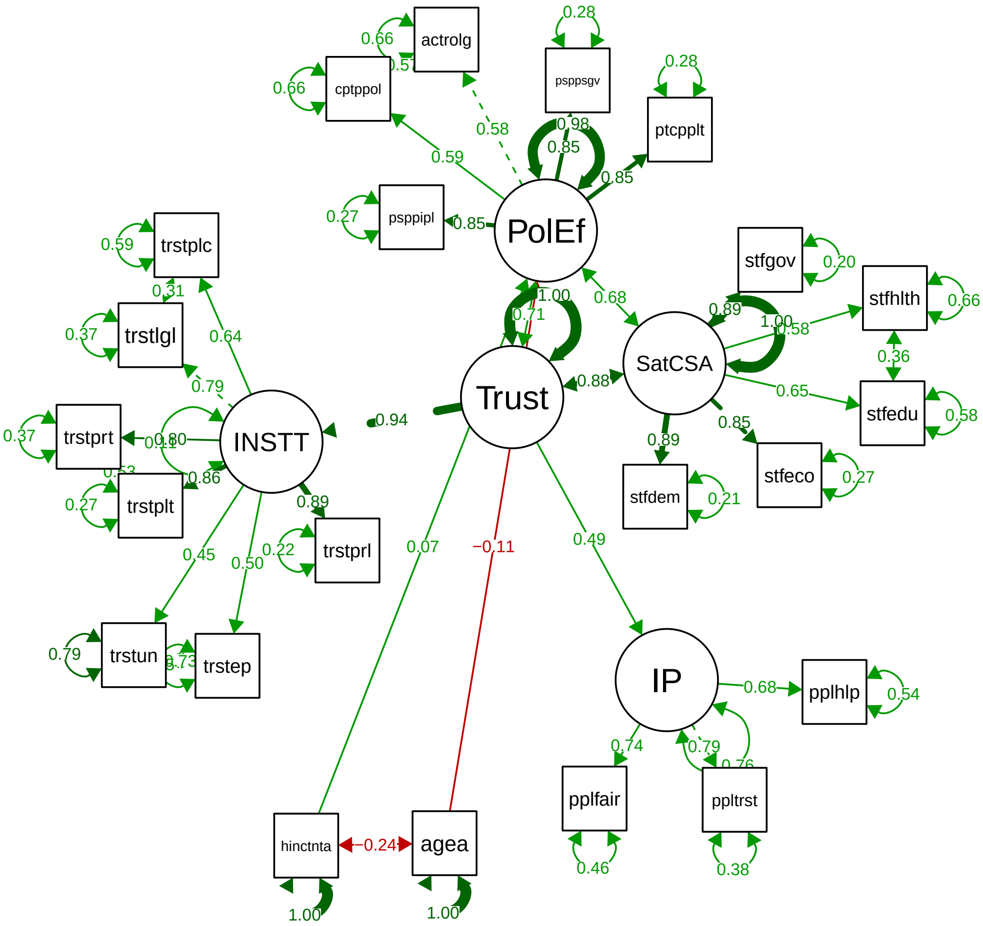

Figure A.57: The MIMIC model, where latent variable Political Efficacy was regressed on Income and Age.

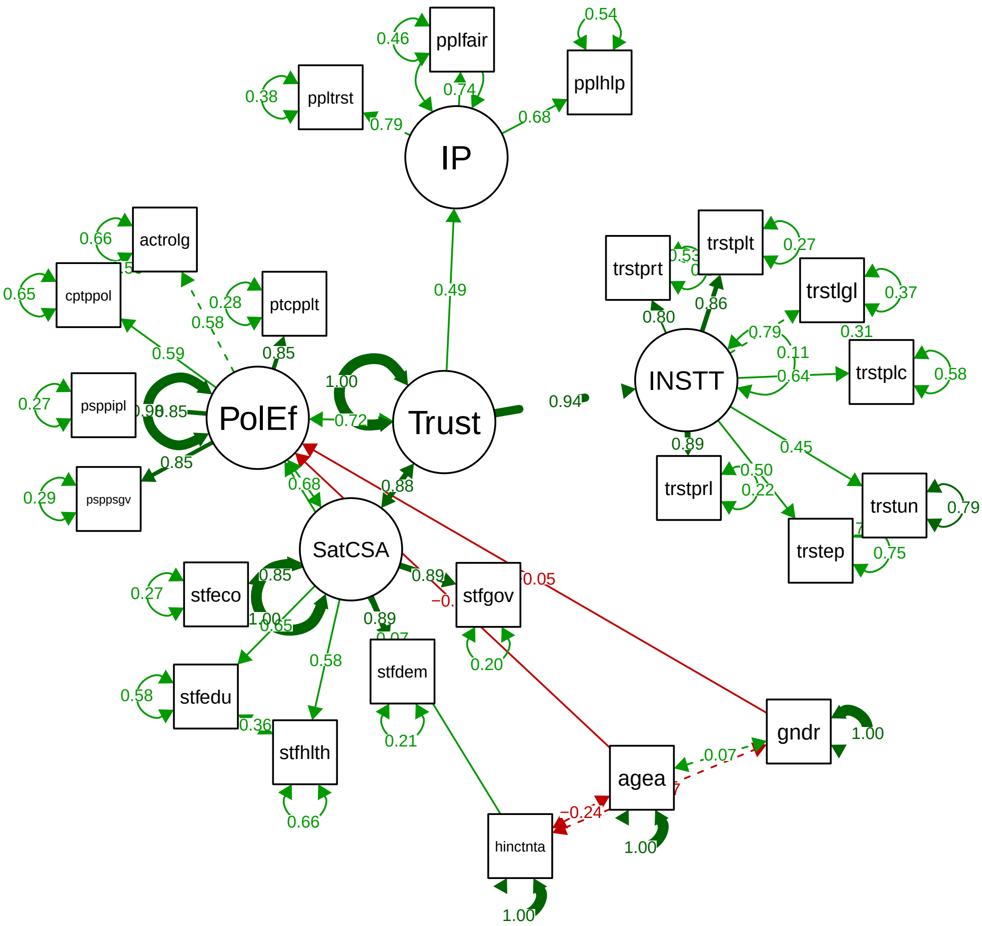

Figure A.58: The MIMIC model, where latent variable Political Efficacy was regressed on Income, Age and Gender.

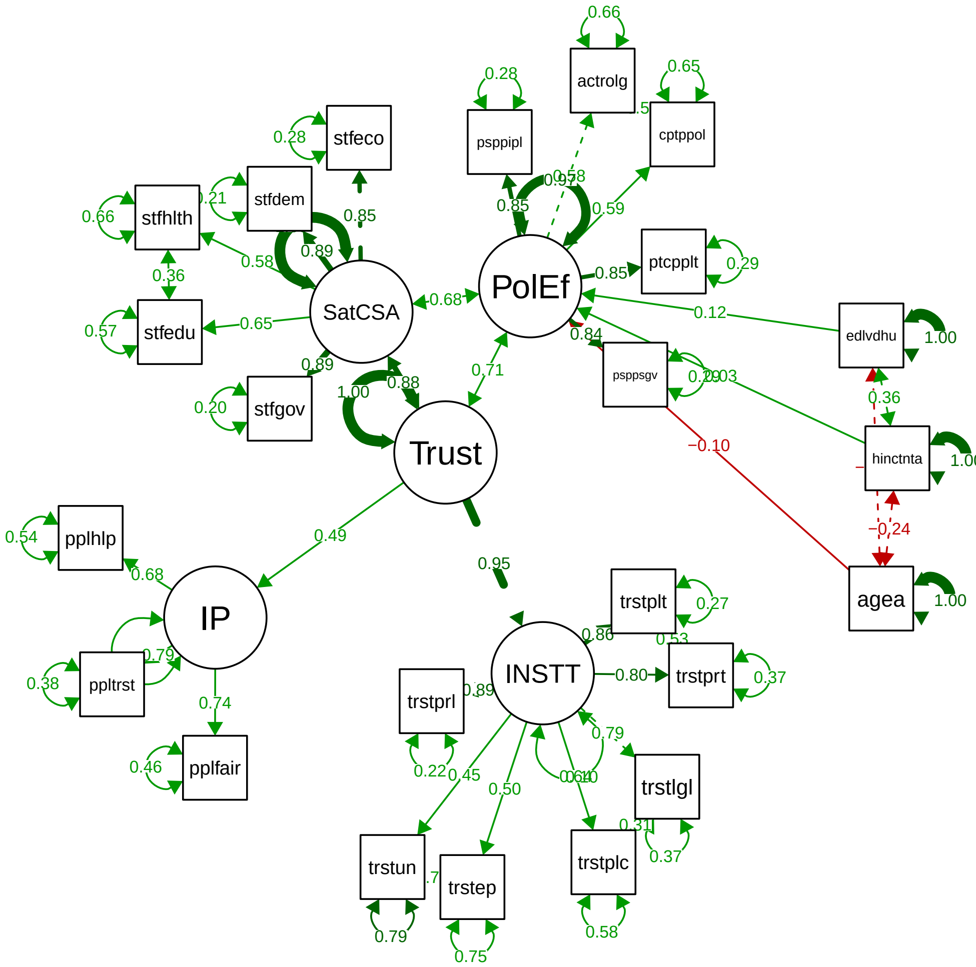

Figure A.59: The MIMIC model, where latent variable Political Efficacy was regressed on Income, Age and Education.

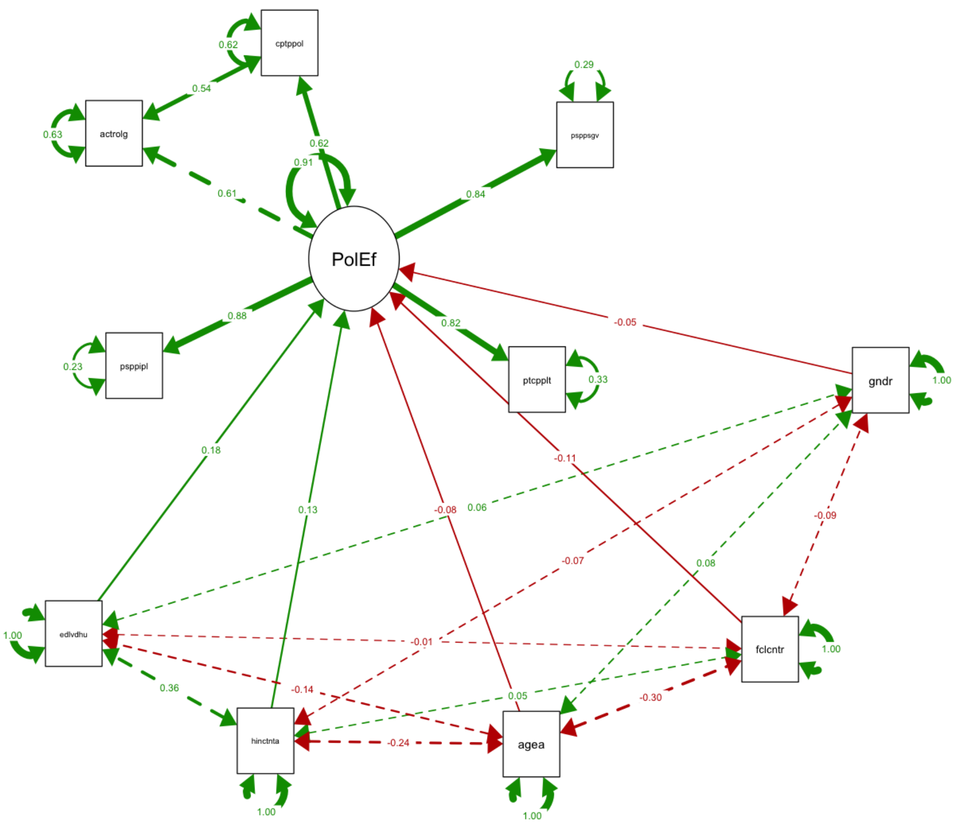

Figure A.60: The MIMIC model, where latent variable Political Efficacy was regressed on all sociodemographic factors.

Mediation model path plots

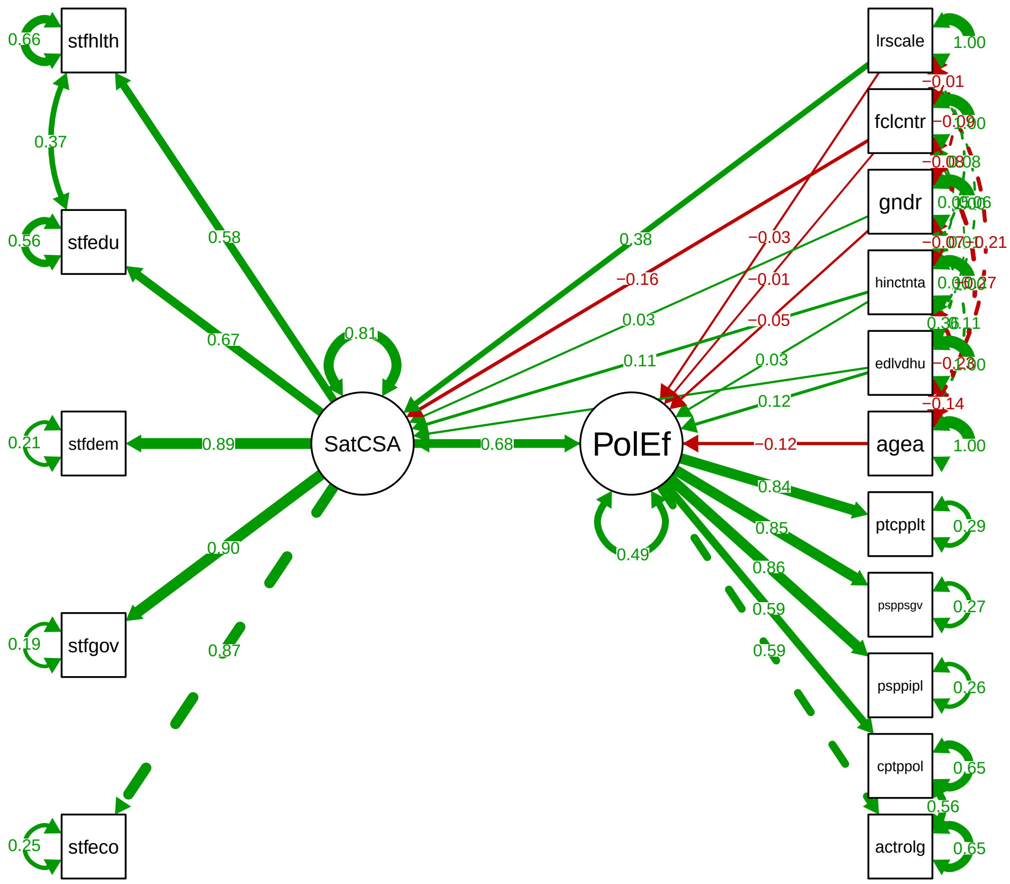

Figure A.61: Mediation model between SatCSA and PolEf

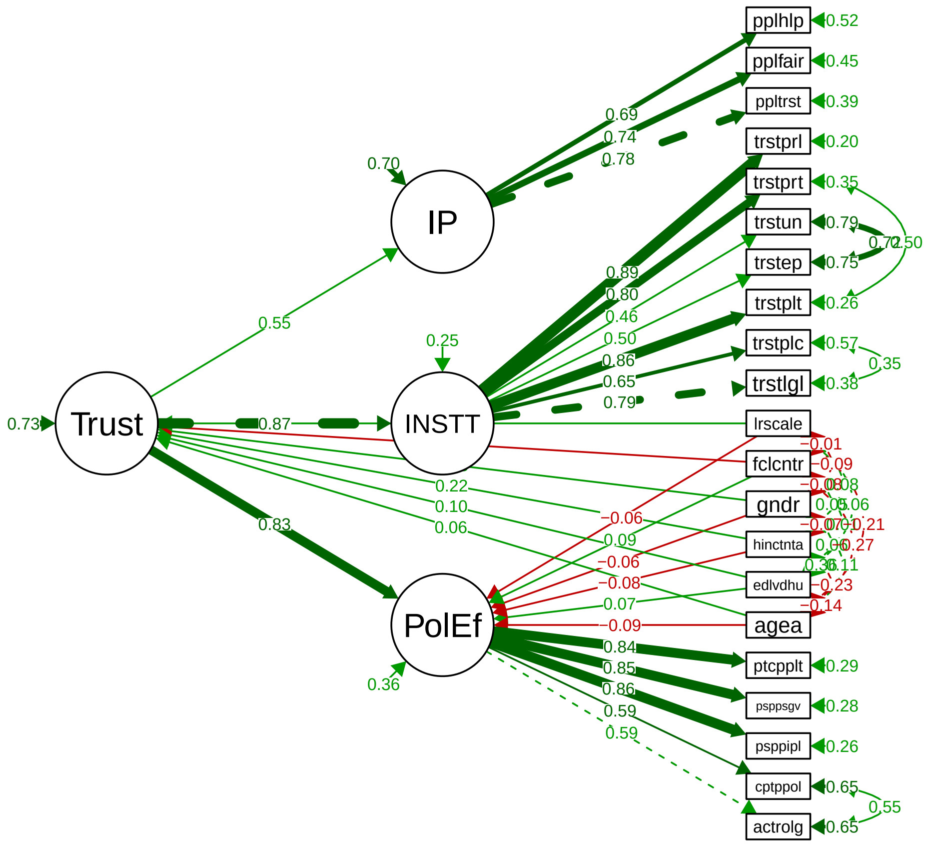

Figure A.62: Mediation model between Trust and PolEf

e R Code

```
# Structural Equations --------------------------------------------------------------------------------
# Description: Assignment
# Author: Lili Vandermeersch r0691855
#
#
#
# Paths --------------------------------------------------------------------------------------------------
rm(list =ls()) # clears R environment
options(scipen=999) # disables scientific notation

setwd('/Users/lilivandermeersch/Library/Mobile Documents/com~apple~CloudDocs/❤️ MSc
Statistics and Data Science ❤️/🌼🌸 Year 3./II./SEM/Assignment')
# input <- file.path(file.choose())
# output <- file.path("/Users/lilivandermeersch/Library/Mobile
Documents/com~apple~CloudDocs/❤️ MSc Statistics and Data Science ❤️/🌼🌸 Year
3./II./SEM/Assignment/plots")

# Packages ---------------------------------------------------------------------------------------------

### DATA MANIPULATION ###
library(rio)
library(dplyr)
library(psych)
library(stringr)
library(purrr)

### MODELING ###
library(lavaan)
library(MVN)
library(Amelia)
library(mice)
# library(semTools)
library(naniar)

### VISUALIZATION ###
library(tidySEM)
library(ggplot2)
library(GGally)
library(semPlot)
library(patchwork)
library(Hmisc)

### CONFLICTED ###
# library(conflicted)

##########################################################################################
# Importing the data
ess_df <- import("/Users/lilivandermeersch/Library/Mobile Documents/com~apple~CloudDocs/❤️
MSc Statistics and Data Science ❤️/🌼🌸 Year 3./II./SEM/Assignment/ESS7/Sav/ESS7.sav")
# Data Exploration ----------------------------------------------------------------
View(ess_df)
```

```
ess_df <- import("/Users/lilivandermeersch/Library/Mobile
Documents/com~apple~CloudDocs/❤️ MSc Statistics and Data Science ❤️/🌼🌸 Year
3./II./SEM/Assignment/ESS7/Sav/ESS7.sav")

# Data Exploration -----------------------------------------------------------------------------------
View(ess_df)
nrow(ess_df)     # number of subjects
ncol(ess_df)     # number of variables
names(ess_df)    # names of variables

# Filter for country
ess_df <- filter(ess_df, cntry == 'HU')
# ess_df <- filter(ess_df, cntry == 'BE')

# Sub-setting the data
ess_df_selected <- ess_df %>% select(
# Political Efficacy
  actrolg, # Able to take active role in political group
  cptppol, # Confident in own ability to participate in politics
  psppipl, # Political system allows people to have influence on politics
  psppsgv, # Political system allows people to have a say in what government does
  ptcpplt, # Politicians care what people think
# Satisfaction with current state of affairs
  stfeco, # How satisfied with present state of economy in country
  stfgov, # How satisfied with the national government
  stfdem, # How satisfied with the way democracy works in country
  stfedu, # How satisfied with state of education in country nowadays
  stfhlth, # How satisfied with state of health services in country nowadays
# Interpersonal trust
  ppltrst, # Most people can be trusted or you can't be too careful
  pplfair,  # Most people try to take advantage of you, or try to be fair
  pplhlp, # Most of the time people helpful or mostly looking out for themselves
# Institutional trust
  trstlgl, # Trust in the legal system
  trstplc, # Trust in the police
  trstplt, # Trust in politicians
  trstep, # Trust in the European Parliament
  trstun, # Trust in the United Nations
  trstprt, # Trust in political parties
  trstprl, # Trust in country's parliament
# Miscellaneous
  fclcntr, # Feel close to country
  lrscale, # Placement on left right scale
# Socio-demographic variables
  edlvdhu, # Highest level of education
  gndr, # Gender
  hinctnta, # Income
```

```
  eduyrs, # Education in years
  agea # Age
)

# Structure and summary of data
str(ess_df_selected)
ess_df_selected %>% glimpse()
summary(ess_df_selected)
# Highest level of education has odd values => Remove 5555 "other"
ess_df_selected["edlvdhu"][ess_df_selected["edlvdhu"] == 5555] <- NA
table(ess_df_selected$gndr)

descriptive_ess <- as.data.frame(psych::describe(ess_df_selected))

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

descriptive_ess
# Handling missing data --------------------------------------------------------------------------------------
na_counts <- colSums(is.na(ess_df_selected))
na_counts

pdf("md.pattern.pdf")
md.pattern(ess_df_selected, rotate.names = TRUE) # pattern of missing data
dev.off()

# Significant number (proportionally) of missing data. Can't be sure if all MCAR or even MAR
# => in fact probably not => ***list wise*** deletion not recommended, might introduce
bias and decrease stat power.
# If using WLS and WLSMV, we can't use full-information maximum-likelihood to deal with
missing data (since they take complete cases).
# One rubbish solution is to use missing='pairwise', which estimates based on pairwise
availability. =>
# => Must use multiple imputation if we include less-then 5-point scales.
# => We will use 5+ point scales. The sample size is large => FIML to handle missing data,
ML/MLM as estimator.

### Filtering out unreliable data ###
# Missing function
percent_missing <- function(x){sum(is.na(x))/length(x)*100}
```

```
# Rows - Unit non-response
missing_rows <- apply(ess_df_selected, 1, percent_missing) # 1 is for rows
table(missing_rows)
# Rows to exclude:
rows_less30 <- subset(ess_df_selected, missing_rows <= 30) # people whose missing data
we can replace
rows_more30<- subset(ess_df_selected, missing_rows > 30) # people who have too much
missing data

#----------------------------------------------------------
# Columns - Item non-response
ess_df_selected_n <- ess_df_selected[sapply(ess_df_selected, is.numeric)]
missing_col <- apply(ess_df_selected_n, 2, percent_missing)
table(missing_col)

ess_df_selected <- rows_less30
################################################################################
# Filtering out careless respondents -------------------------------------------------------------------------
# Calculate the Mahalanobis distance for each respondent
# mahalanobis_distances <- mahalanobis(ess_df_selected, center =
colMeans(ess_df_selected), cov = cov(ess_df_selected))

# Add the Mahalanobis distances to the dataset
# ess_df_selected$Mahalanobis <- mahalanobis_distances

# Set a threshold for flagging potential careless respondents
# You can adjust the threshold depending on your data and specific needs
# threshold <- qchisq(0.001, df = ncol(ess_df_selected), lower.tail = FALSE)

# Flag respondents with Mahalanobis distances above the threshold
# careless_respondents <- ess_df_selected$Mahalanobis > threshold

# Filter out the careless respondents
# filtered_data1 <- ess_df_selected[!careless_respondents, ]

# No apparent careless respondents to filter out!

################################################################################
# MODEL ASSUMPTIONS --------------------------------------------------------------------------------------------
# 1. Multivariate normality
# Non-normality doesn't affect the parameter estimates that much but it does affect the X2s
and the SEs.
# Effects will appear statistically significant when in fact they are not.

# Histograms
# List of your variables
variables <- names(ess_df_selected)
```

```
# => Must use multiple imputation if we include less-then 5-point scales.
# => We will use 5+ point scales. The sample size is large => FIML to handle missing data, ML/MLM as
estimatoor.

### Filtering out unreliable data ###
# Missing function
percent_missing <- function(x){sum(is.na(x))/length(x)*100}
# Rows - Unit non-response
missing_rows <- apply(ess_df_selected, 1, percent_missing) # 1 is for rows
table(missing_rows)
# Rows to exclude:
rows_less50 <- subset(ess_df_selected, missing_rows <= 50) # people whose missing data we can
replace
rows_more50<- subset(ess_df_selected, missing_rows > 50) # people who have too much missing
data

#-------------------
# Columns - Item non-response
ess_df_selected_n <- ess_df_selected[sapply(ess_df_selected, is.numeric)]
missing_col <- apply(ess_df_selected_n, 2, percent_missing)
table(missing_col)

ess_df_selected <- rows_less50
################################################################################
# Filtering out careless respondents -----------------------------------------------
# Calculate the Mahalanobis distance for each respondent
# mahalanobis_distances <- mahalanobis(ess_df_selected, center = colMeans(ess_df_selected), cov
= cov(ess_df_selected))

# Add the Mahalanobis distances to the dataset
# ess_df_selected$Mahalanobis <- mahalanobis_distances

# Set a threshold for flagging potential careless respondents
# You can adjust the threshold depending on your data and specific needs
# threshold <- qchisq(0.001, df = ncol(ess_df_selected), lower.tail = FALSE)

# Flag respondents with Mahalanobis distances above the threshold
# careless_respondents <- ess_df_selected$Mahalanobis > threshold

# Filter out the careless respondents
# filtered_data1 <- ess_df_selected[!careless_respondents, ]

# Nothing to filter out!

################################################################################
# MODEL ASSUMPTIONS -----------------------------------------------------------
# 1. Multivariate normality
# Non-normality doesn't affect the parameter estimates that much but it does affect the X2s and the
SEs.
# Effects will appear statistically significant when in fact they are not.
```

```
# Histograms
# List of your variables
variables <- names(ess_df_selected)

for (var in variables) {
  hist(ess_df_selected[[var]], main=var, xlab="Value", breaks="FD") # "FD" is Freedman-Diaconis rule
and it's good for most cases
}

hist.data.frame(ess_df_selected)

# Checking univariate normality using Shapiro-Wilk instead of Kolmogorov-Smirnov, as it is more
robust to 'ties'.
# Although with large n even small deviations give significant results
# Function Shapiro-Wilk
shapiro_test_single_var <- function(data, var_name){
  shapiro_test_result <- shapiro.test(data[[var_name]][!is.na(data[[var_name]])])
  return(list("Variable" = var_name,
        "W" = round(shapiro_test_result$statistic, 2),
        "P-value" = shapiro_test_result$p.value))
}
var_names <- names(ess_df_selected_lf)
shapiro_test_results <- lapply(var_names, function(var_name)
shapiro_test_single_var(ess_df_selected, var_name))

shapiro_test_results_df <- do.call(rbind, lapply(shapiro_test_results, as.data.frame))
shapiro_test_results_df # gives W statistic and p-values for each variables (H0: normal distr.)
#-----------------------------------------------------------------------------
# Calculating the multivariate kurtosis and skewness
mvn_test <- mvn(data = ess_df_selected_lf, # our data
         mvnTest = c("hz")    # type of normality test to perform
)

mvn_test$multivariateNormality # not multivariate normal => Use "Robust" estimator (MLM)
# To mitigate non-normality we can use scaled χ2 and "robust" standard errors corrections to ML
estimation
# as in Satorra and Bentler (1988; 1994).
# Adjustments are made to the χ2 (and χ2 based fit indices) and standard errors based on a weight
matrix
# derived from an estimate of multivariate kurtosis (as said before, the parameter estimates
themselves
# are not altered).

# 2. Linearity => to be assessed once CFA and SEM models fit

# 3. Independence of observations
# # Random sampling => we can assume that the observations are independent.

# 4. Adequate sample size
# Generally, sample sizes greater than 200 are considered adequate for CFA.
n <- nrow(ess_df_selected)
```

```
cat("Sample size:", n)

###########################################################################
          ### CFA - Measurement part ###
###########################################################################
### Political Efficacy ###
#####################

cfa_model_PolEf <- '
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
'

fit_cfa_PolEf <- cfa(cfa_model_PolEf,
                     data = ess_df_selected,
                     missing = "direct",     # alias: "ml" or "fiml"
                     estimator = "ML")

summary(fit_cfa_PolEf,
    fit.measures = TRUE,
    standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_PolEf, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_PolEf,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#-------------------------------------------------------------------------
cfa_model_PolEf2 <- '
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol
'

fit_cfa_PolEf2 <- cfa(cfa_model_PolEf2,
              data = ess_df_selected,
              missing = "direct",     # alias: "ml" or "fiml"
              estimator = "ML")

summary(fit_cfa_PolEf2,
    fit.measures = TRUE,
    standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_PolEf2, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_PolEf2,"mi")
```

```
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#------------------------------------------------------------------------------
cfa_model_PolEf3 <- '
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol
psppsgv ~~ ptcpplt
'

fit_cfa_PolEf3 <- cfa(cfa_model_PolEf3,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_PolEf3,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_PolEf3, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_PolEf3,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

########################################################################################
### Satisfaction with current state of affairs ###
##########################################

cfa_model_SatCSA <- '
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
'

fit_cfa_SatCSA <- cfa(cfa_model_SatCSA ,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_SatCSA,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_SatCSA, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_SatCSA,"mi")
```

```
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#------------------------------------------------------------------------------

cfa_model_SatCSA2 <- '
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
stfedu ~~ stfhlth
'

fit_cfa_SatCSA2 <- cfa(cfa_model_SatCSA2 ,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_SatCSA2,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_SatCSA2, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_SatCSA2,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#------------------------------------------------------------------------------
cfa_model_SatCSA3 <- '
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
stfedu ~~ stfhlth
stfeco ~~ stfgov
'

fit_cfa_SatCSA3 <- cfa(cfa_model_SatCSA3 ,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_SatCSA3,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_SatCSA3, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_SatCSA3,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
```

```
mi.sorted[1:5,] # only display some large MI values

##################################################################################
### Interpersonal trust ###
########################
cfa_model_IPT <- '
IP =~ ppltrst + pplfair + pplhlp
'

fit_cfa_IPT <- cfa(cfa_model_IPT,
            data = ess_df_selected,
            missing = "direct",      # alias: "ml" or "fiml"
            estimator = "ML")

summary(fit_cfa_IPT,
      fit.measures = TRUE,
      standardized = TRUE
)

fitMeasures(fit_cfa_IPT, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")

##################################################################################
### Institutional trust ###
######################

cfa_model_INSTT <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
'

fit_cfa_INSTT <- cfa(cfa_model_INSTT,
            data = ess_df_selected,
            missing = "direct",      # alias: "ml" or "fiml"
            estimator = "ML")

summary(fit_cfa_INSTT,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_INSTT, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_INSTT,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#--------------------------------------------------------------------------------
cfa_model_INSTT2 <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
```

```
trstplt ~~ trstprt
'

fit_cfa_INSTT2 <- cfa(cfa_model_INSTT2,
            data = ess_df_selected,
            missing = "direct",     # alias: "ml" or "fiml"
            estimator = "ML")

summary(fit_cfa_INSTT2,
    fit.measures = TRUE,
    standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_INSTT2, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_INSTT2,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#---------------------------------------------------------------------------------
cfa_model_INSTT3 <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
trstplt ~~ trstprt
trstep ~~  trstun
'

fit_cfa_INSTT3 <- cfa(cfa_model_INSTT3,
            data = ess_df_selected,
            missing = "direct",     # alias: "ml" or "fiml"
            estimator = "ML")

summary(fit_cfa_INSTT3,
    fit.measures = TRUE,
    standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_INSTT3, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_INSTT3,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#---------------------------------------------------------------------------------
cfa_model_INSTT4 <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
trstplt ~~ trstprt
trstep ~~  trstun
```

```
trstlgl ~~ trstplc
'

fit_cfa_INSTT4 <- cfa(cfa_model_INSTT4,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_INSTT4,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_INSTT4, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_INSTT4,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

##########################################################################################
### Trust ###
###########
cfa_model_Trust <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
'

fit_cfa_Trust <- cfa(cfa_model_Trust,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_Trust,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_Trust, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_Trust,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#--------------------------------------------------------------------------------
cfa_model_Trust2 <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
```

```
trstplt ~~ trstprt
'

fit_cfa_Trust2 <- cfa(cfa_model_Trust2,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_Trust2,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_Trust2, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_Trust2,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#-------------------------------------------------------------------------------
cfa_model_Trust3 <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
trstplt ~~ trstprt
trstep ~~  trstun
'

fit_cfa_Trust3 <- cfa(cfa_model_Trust3,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_Trust3,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_Trust3, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_Trust3,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

#-------------------------------------------------------------------------------
cfa_model_Trust4 <- '
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
```

```
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
'

fit_cfa_Trust4 <- cfa(cfa_model_Trust4,
                data = ess_df_selected,
                missing = "direct",      # alias: "ml" or "fiml"
                estimator = "ML")

summary(fit_cfa_Trust4,
      fit.measures = TRUE,
      standardized = TRUE
)

# Global fit
fitMeasures(fit_cfa_Trust4, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_cfa_Trust4,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

semPaths(fit_cfa_Trust4)

##########################################################################################
### Complete Measurement Model ###
##################################
cfa_model_POL <- '
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol
'

fit_cfa_POL <- cfa(cfa_model_POL,
            estimator = "ML",
            missing = 'direct',
            data = ess_df_selected
)

summary(fit_cfa_POL,
      fit.measures = TRUE,
```

```
    standardized = TRUE
)

fitMeasures(fit_cfa_POL, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")

# Visualization
semPaths(fit_cfa_POL, what = "std", optimizeLatRes = TRUE, layout = "tree", nCharNodes = 0,
intercepts = FALSE, fade = FALSE)

# Alternatively
lay <- get_layout("stfeco", "stfgov", "stfdem", "stfedu", "stfhlth", "actrolg", "cptppol", "psppipl",
"psppsgv", "ptcpplt",
        "","","Trust","","SatCSA", "", "" ,"PolEf", "", "",
        "", "", "", "INSTT", "", "", "IP", "", "", "",
        "trstlgl", "trstplc", "trstplt", "trstep", "trstun", "trstprt", "trstprl", "ppltrst", "pplfair",
"pplhlp", rows = 4)
lay

plot_POL <- graph_sem(model = fit_cfa_POL,
          #label = "est_std",
          layout = lay,
          angle = 170
)

plot_POL

######################################################################################
### Checking Linearity ###------------------------------------------------------------------------
# Extracting factor scores
factor_values <- data.frame(lavPredict(fit_cfa_POL))
head(factor_values)
## Trust-------------------------------------------------------------------------
trust_df <- as.data.frame(cbind(factor_values$Trust, factor_values$INSTT, factor_values$IP))
trust_df <- trust_df %>%
  rename("Trust" = "V1" ,
      "INSTT" = "V2",
      "IP" = "V3")

head(trust_df)

ggpairs(trust_df, aes(color = as.factor(ess_df_selected$gndr), alpha = 0.5), lower = list(continuous =
"smooth"))

pairs(trust_df)

## Sat CSA -------------------------------------------------------------------------------

sat_csa_df <- as.data.frame(cbind(factor_values$SatCSA, ess_df_selected$stfeco,
                ess_df_selected$stfgov, ess_df_selected$stfdem,
                ess_df_selected$stfedu, ess_df_selected$stfhlth))
```

```
sat_csa_df <- sat_csa_df %>%
  rename("Sat_CSA" = "V1" ,
        "stfeco" = "V2",
        "stfgov" = "V3",
        "stfdem" = "V4",
        "stfedu" = "V5",
        "stdhlth" = "V6")

head(sat_csa_df)

ggpairs(sat_csa_df, aes(color = as.factor(ess_df_selected$gndr), alpha = 0.5), lower = list(continuous
= "smooth"))

pairs(sat_csa_df)

## IP ---------------------------------------------------------------------------

IP_df <- as.data.frame(cbind(factor_values$IP, ess_df_selected$ppltrst,ess_df_selected$pplhlp,
ess_df_selected$pplfair))
IP_df <- IP_df %>%
  rename("IP" = "V1" ,
        "ppltrst" = "V2",
        "pplhlp" = "V3",
        "pplfair" = "V4")

head(IP_df)

ggpairs(IP_df, aes(color = as.factor(ess_df_selected$gndr), alpha = 0.5), lower = list(continuous =
"smooth"))

pairs(IP_df)

## ISTT ---------------------------------------------------------------------------

INSTT_df <- as.data.frame(cbind(factor_values$INSTT,
ess_df_selected$trstlgl,ess_df_selected$trstplc, ess_df_selected$trstplt,
                        ess_df_selected$trstprl,ess_df_selected$trstep, ess_df_selected$trstun,
                        ess_df_selected$trstprt))
INSTT_df <- INSTT_df %>%
  rename("INSTT" = "V1" ,
        "trstlgl" = "V2",
        "trstplc" = "V3",
        "trstplt" = "V4",
        "trstprl" = "V5",
        "trstep" = "V6",
        "trstun" = "V7",
        "trstprt" = "V8")

head(INSTT_df)
```

```
ggpairs(INSTT_df, aes(color = as.factor(ess_df_selected$gndr), alpha = 0.5), lower = list(continuous =
"smooth"))

pairs(INSTT_df)

## PolEf ---------------------------------------------------------------------------

PolEf_df <- as.data.frame(cbind(factor_values$PolEf, ess_df_selected$actrolg,
                         ess_df_selected$cptppol, ess_df_selected$psppipl,
                         ess_df_selected$psppsgv,ess_df_selected$ptcpplt))
PolEf_df <- PolEf_df %>%
  rename("PolEf" = "V1" ,
        "actrolg" = "V2",
        "cptppol" = "V3",
        "psppipl" = "V4",
        "psppsgv" = "V5",
        "ptcpplt" = "V6")

head(PolEf_df)

ggpairs(PolEf_df, aes(color = as.factor(ess_df_selected$gndr), alpha = 0.5), lower = list(continuous =
"smooth"))

pairs(PolEf_df)

##########################################################################################
# Model Diagnostics Comparison ------------------------------------------------------------
# anova() only works with estimator = "ML"

# INSTT
anova(fit_cfa_INSTT, fit_cfa_INSTT2)
anova(fit_cfa_INSTT2, fit_cfa_INSTT3)
anova(fit_cfa_INSTT3, fit_cfa_INSTT4)

# Trust
anova(fit_cfa_Trust, fit_cfa_Trust2)
anova(fit_cfa_Trust2, fit_cfa_Trust3)
anova(fit_cfa_Trust3, fit_cfa_Trust4)

# SatCSA
anova(fit_cfa_SatCSA, fit_cfa_SatCSA2)
anova(fit_cfa_SatCSA2, fit_cfa_SatCSA3)

# PolEf
anova(fit_cfa_PolEf, fit_cfa_PolEf2)
anova(fit_cfa_PolEf2, fit_cfa_PolEf3)

fit_indicesINSTT <- data.frame(
  fit_cfa_INSTT = c(round(fitMeasures(fit_cfa_INSTT)["logl"], 2),
round(fitMeasures(fit_cfa_INSTT)["chisq"], 2), round(fitMeasures(fit_cfa_INSTT)["df"], 2),
```

```
round(fitMeasures(fit_cfa_INSTT)["pvalue"], 2), round(fitMeasures(fit_cfa_INSTT)["cfi"], 2),
round(fitMeasures(fit_cfa_INSTT)["tli"], 2), round(fitMeasures(fit_cfa_INSTT)["rmsea"], 2)),
  fit_cfa_INSTT2 = c(round(fitMeasures(fit_cfa_INSTT2)["logl"], 2),
round(fitMeasures(fit_cfa_INSTT2)["chisq"], 2), round(fitMeasures(fit_cfa_INSTT2)["df"], 2),
round(fitMeasures(fit_cfa_INSTT2)["pvalue"], 2), round(fitMeasures(fit_cfa_INSTT2)["cfi"], 2),
round(fitMeasures(fit_cfa_INSTT2)["tli"], 2), round(fitMeasures(fit_cfa_INSTT2)["rmsea"], 2)),
  fit_cfa_INSTT3 = c(round(fitMeasures(fit_cfa_INSTT3)["logl"], 2),
round(fitMeasures(fit_cfa_INSTT3)["chisq"], 2), round(fitMeasures(fit_cfa_INSTT3)["df"], 2),
round(fitMeasures(fit_cfa_INSTT3)["pvalue"], 2), round(fitMeasures(fit_cfa_INSTT3)["cfi"], 2),
round(fitMeasures(fit_cfa_INSTT3)["tli"], 2), round(fitMeasures(fit_cfa_INSTT3)["rmsea"], 2)),
  fit_cfa_INSTT4 = c(round(fitMeasures(fit_cfa_INSTT4)["logl"], 2),
round(fitMeasures(fit_cfa_INSTT4)["chisq"], 2), round(fitMeasures(fit_cfa_INSTT4)["df"], 2),
round(fitMeasures(fit_cfa_INSTT4)["pvalue"], 2), round(fitMeasures(fit_cfa_INSTT4)["cfi"], 2),
round(fitMeasures(fit_cfa_INSTT4)["tli"], 2), round(fitMeasures(fit_cfa_INSTT4)["rmsea"], 2))
)
fit_indicesINSTT

fit_indicesTrust <- data.frame(
  fit_cfa_Trust = c(round(fitMeasures(fit_cfa_Trust)["logl"], 2),
round(fitMeasures(fit_cfa_Trust)["chisq"], 2), round(fitMeasures(fit_cfa_Trust)["df"], 2),
round(fitMeasures(fit_cfa_Trust)["pvalue"], 2), round(fitMeasures(fit_cfa_Trust)["cfi"], 2),
round(fitMeasures(fit_cfa_Trust)["tli"], 2), round(fitMeasures(fit_cfa_Trust)["rmsea"], 2)),
  fit_cfa_Trust2 = c(round(fitMeasures(fit_cfa_Trust2)["logl"], 2),
round(fitMeasures(fit_cfa_Trust2)["chisq"], 2), round(fitMeasures(fit_cfa_Trust2)["df"], 2),
round(fitMeasures(fit_cfa_Trust2)["pvalue"], 2), round(fitMeasures(fit_cfa_Trust2)["cfi"], 2),
round(fitMeasures(fit_cfa_Trust2)["tli"], 2), round(fitMeasures(fit_cfa_Trust2)["rmsea"], 2)),
  fit_cfa_Trust3 = c(round(fitMeasures(fit_cfa_Trust3)["logl"], 2),
round(fitMeasures(fit_cfa_Trust3)["chisq"], 2), round(fitMeasures(fit_cfa_Trust3)["df"], 2),
round(fitMeasures(fit_cfa_Trust3)["pvalue"], 2), round(fitMeasures(fit_cfa_Trust3)["cfi"], 2),
round(fitMeasures(fit_cfa_Trust3)["tli"], 2), round(fitMeasures(fit_cfa_Trust3)["rmsea"], 2)),
  fit_cfa_Trust4 = c(round(fitMeasures(fit_cfa_Trust4)["logl"], 2),
round(fitMeasures(fit_cfa_Trust4)["chisq"], 2), round(fitMeasures(fit_cfa_Trust4)["df"], 2),
round(fitMeasures(fit_cfa_Trust4)["pvalue"], 2), round(fitMeasures(fit_cfa_Trust4)["cfi"], 2),
round(fitMeasures(fit_cfa_Trust4)["tli"], 2), round(fitMeasures(fit_cfa_Trust4)["rmsea"], 2))
)
fit_indicesTrust


fit_indicesSatCSA <- data.frame(
  fit_cfa_SatCSA = c(round(fitMeasures(fit_cfa_SatCSA)["logl"], 2),
round(fitMeasures(fit_cfa_SatCSA)["chisq"], 2), round(fitMeasures(fit_cfa_SatCSA)["df"], 2),
round(fitMeasures(fit_cfa_SatCSA)["pvalue"], 2), round(fitMeasures(fit_cfa_SatCSA)["cfi"], 2),
round(fitMeasures(fit_cfa_SatCSA)["tli"], 2), round(fitMeasures(fit_cfa_SatCSA)["rmsea"], 2)),
  fit_cfa_SatCSA2 = c(round(fitMeasures(fit_cfa_SatCSA2)["logl"], 2),
round(fitMeasures(fit_cfa_SatCSA2)["chisq"], 2), round(fitMeasures(fit_cfa_SatCSA2)["df"], 2),
round(fitMeasures(fit_cfa_SatCSA2)["pvalue"], 2), round(fitMeasures(fit_cfa_SatCSA2)["cfi"], 2),
round(fitMeasures(fit_cfa_SatCSA2)["tli"], 2), round(fitMeasures(fit_cfa_SatCSA2)["rmsea"], 2)),
  fit_cfa_SatCSA3 = c(round(fitMeasures(fit_cfa_SatCSA3)["logl"], 2),
round(fitMeasures(fit_cfa_SatCSA3)["chisq"], 2), round(fitMeasures(fit_cfa_SatCSA3)["df"], 2),
round(fitMeasures(fit_cfa_SatCSA3)["pvalue"], 2), round(fitMeasures(fit_cfa_SatCSA3)["cfi"], 2),
round(fitMeasures(fit_cfa_SatCSA3)["tli"], 2), round(fitMeasures(fit_cfa_SatCSA3)["rmsea"], 2))
```

```
)
fit_indicesSatCSA


fit_indicesPolEf <- data.frame(
  fit_cfa_PolEf = c(round(fitMeasures(fit_cfa_PolEf)["logl"], 2),
round(fitMeasures(fit_cfa_PolEf)["chisq"], 2), round(fitMeasures(fit_cfa_PolEf)["df"], 2),
round(fitMeasures(fit_cfa_PolEf)["pvalue"], 2), round(fitMeasures(fit_cfa_PolEf)["cfi"], 2),
round(fitMeasures(fit_cfa_PolEf)["tli"], 2), round(fitMeasures(fit_cfa_PolEf)["rmsea"], 2)),
  fit_cfa_PolEf2 = c(round(fitMeasures(fit_cfa_PolEf2)["logl"], 2),
round(fitMeasures(fit_cfa_PolEf2)["chisq"], 2), round(fitMeasures(fit_cfa_PolEf2)["df"], 2),
round(fitMeasures(fit_cfa_PolEf2)["pvalue"], 2), round(fitMeasures(fit_cfa_PolEf2)["cfi"], 2),
round(fitMeasures(fit_cfa_PolEf2)["tli"], 2), round(fitMeasures(fit_cfa_PolEf2)["rmsea"], 2)),
  fit_cfa_PolEf3 = c(round(fitMeasures(fit_cfa_PolEf3)["logl"], 2),
round(fitMeasures(fit_cfa_PolEf3)["chisq"], 2), round(fitMeasures(fit_cfa_PolEf3)["df"], 2),
round(fitMeasures(fit_cfa_PolEf3)["pvalue"], 2), round(fitMeasures(fit_cfa_PolEf3)["cfi"], 2),
round(fitMeasures(fit_cfa_PolEf3)["tli"], 2), round(fitMeasures(fit_cfa_PolEf3)["rmsea"], 2))
 )
fit_indicesPolEf

######################################################################################
                    ### SEM ###
######################################################################################
######################################################################################
### MIMIC #### The more indicators we include => the more restrictions (e.g. that they do not
# effect other latent vars than the ones we associate them.
# Fit usually gets worse and worse, the more
# we include => See Lab 2. Ex.) Investigate why fit is bad => MI
######################################################################################
model_mimic <-'
# Measurement model
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

# Covariances
Trust ~~ SatCSA
PolEf ~~ SatCSA
PolEf ~~ Trust
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol

# MIMIC
PolEf ~ lrscale
'
```

```
### Amelia ###-----------------------------------------------------------------
# Amelia explicitly requires an object of data.frame class
ess_df_selected <- data.frame(ess_df_selected)
# Imputation
a.out <- amelia(ess_df_selected,  # original dataset with missing
           m = 15,    # number of m "completed" data sets
           seed = 222   # set the seed
)
# We can check each "completed" dataset against our original data
cbind(ess_df_selected$hinctnta, a.out$imputations$imp1$hinctnta)[c(75:85),]

# Fitting the model to multiple imputed data sets
fit_mimic_a <- semTools::runMI(
  model = model_mimic,        # model
  data = a.out$imputations, # list of imputed data sets
  fun = "sem",            # lavaan function
  estimator = "MLR"
)

summary(fit_mimic_a, fit.measures = TRUE, standardized = TRUE)

### FIML ###-------------------------------------------------------------------
fit_mimic_fiml <- sem(model_mimic,
             estimator = "ML",
             missing = 'direct',
             data = ess_df_selected
)

summary(fit_mimic_fiml,
      fit.measures = TRUE,
      standardized = TRUE
)

fitm_mimic <- fitMeasures(fit_mimic_fiml, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
fitm_mimic

## Modification Indexes
mi <- inspect(fit_mimic_fiml,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
mi.sorted[1:5,] # only display some large MI values

### COMPARISON ###-------------------------------------------------------------
# let's compare the fit of the different models
model_fit <-  function(lavobject) {
  vars <- c("chisq", "df", "cfi", "tli", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper", "rmsea.pvalue",
"srmr")
  return(fitmeasures(lavobject)[vars] %>% data.frame() %>% round(2) %>% t())
}
```

```
table_fit_mimic <-
  list(model_fit(fit_mimic_fiml),
      model_fit(fit_mimic_a)) %>%
  reduce(rbind)

rownames(table_fit_mimic) <- c("FIML", "Amelia")

table_fit_mimic

# Visualization
semPaths(fit_mimic_fiml, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE)

##################################################################################
model_mimic_e <-'
# Measurement model
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

# Covariances
Trust ~~ SatCSA
PolEf ~~ SatCSA
PolEf ~~ Trust
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol

# MIMIC
PolEf ~ lrscale
psppipl ~ lrscale
psppsgv ~ lrscale
ptcpplt ~ lrscale
'
fit_mimic_fiml_e <- sem(model_mimic_e,
                estimator = "ML",
                missing = 'direct',
                data = ess_df_selected
)

summary(fit_mimic_fiml_e,
      fit.measures = TRUE,
      standardized = TRUE
)
```

```
fitm_mimic_e <- fitMeasures(fit_mimic_fiml_e, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
fitm_mimic_e

## Modification Indexes
mi <- inspect(fit_mimic_fiml_e,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
mi.sorted[1:5,] # only display some large MI values

# Visualization
semPaths(fit_mimic_fiml_e, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE)

###################################################################################
model_mimic2 <-'
# Measurement model
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

# Covariances
Trust ~~ SatCSA
PolEf ~~ SatCSA
PolEf ~~ Trust
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol

# MIMIC
PolEf ~ hinctnta
'

fit_mimic2 <- sem(model_mimic2,
            estimator = "ML",
            missing = 'direct',
            data = ess_df_selected
)

summary(fit_mimic2,
      fit.measures = TRUE,
      standardized = TRUE
)

fitm_mimic2 <- fitMeasures(fit_mimic2, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
```

```
fitm_mimic2

## Modification Indexes
mi <- inspect(fit_mimic2,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
mi.sorted[1:5,] # only display some large MI values

# Visualization
semPaths(fit_mimic2, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE)

######################################################################################
model_mimic3 <-'
# Measurement model
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

# Covariances
Trust ~~ SatCSA
PolEf ~~ SatCSA
PolEf ~~ Trust
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol

# MIMIC
PolEf ~ hinctnta + fclcntr
'

fit_mimic3 <- sem(model_mimic3,
            estimator = "ML",
            missing = 'direct',
            data = ess_df_selected
)

summary(fit_mimic3,
      fit.measures = TRUE,
      standardized = TRUE
)

fitm_mimic3 <- fitMeasures(fit_mimic3, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
fitm_mimic3
```

```
## Modification Indexes
mi <- inspect(fit_mimic3,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
mi.sorted[1:5,] # only display some large MI values

# Visualization
semPaths(fit_mimic3, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE)

#######################################################################################
model_mimic4 <-'
# Measurement model
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

# Covariances
Trust ~~ SatCSA
PolEf ~~ SatCSA
PolEf ~~ Trust
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol

# MIMIC
PolEf ~ hinctnta + agea
'

fit_mimic4 <- sem(model_mimic4,
            estimator = "ML",
            missing = 'direct',
            data = ess_df_selected
)

summary(fit_mimic4,
      fit.measures = TRUE,
      standardized = TRUE
)

fitm_mimic4 <- fitMeasures(fit_mimic4, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
fitm_mimic4

## Modification Indexes
mi <- inspect(fit_mimic4,"mi")
```

```
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
mi.sorted[1:5,] # only display some large MI values

# Visualization
semPaths(fit_mimic4, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE, rotation = 2)

##################################################################################
model_mimic5 <-'
# Measurement model
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

# Covariances
Trust ~~ SatCSA
PolEf ~~ SatCSA
PolEf ~~ Trust
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol

# MIMIC
PolEf ~ hinctnta + agea + gndr
'

fit_mimic5 <- sem(model_mimic5,
            estimator = "ML",
            missing = 'direct',
            data = ess_df_selected
)

summary(fit_mimic5,
      fit.measures = TRUE,
      standardized = TRUE
)

fitm_mimic5 <- fitMeasures(fit_mimic5, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
fitm_mimic5

## Modification Indexes
mi <- inspect(fit_mimic5,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
```

```
mi.sorted[1:5,] # only display some large MI values

# Visualization
semPaths(fit_mimic5, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE)

##########################################################################################
model_mimic6 <-'
# Measurement model
Trust =~ INSTT + IP
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt

INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp

# Covariances
Trust ~~ SatCSA
PolEf ~~ SatCSA
PolEf ~~ Trust
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc
stfedu ~~ stfhlth
actrolg ~~ cptppol

# MIMIC
PolEf ~ hinctnta + agea + edlvdhu
'

fit_mimic6 <- sem(model_mimic6,
           estimator = "ML",
           missing = 'direct',
           data = ess_df_selected
)

summary(fit_mimic6,
      fit.measures = TRUE,
      standardized = TRUE
)

fitm_mimic6 <- fitMeasures(fit_mimic6, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
fitm_mimic6

## Modification Indexes
mi <- inspect(fit_mimic6,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
mi.sorted[1:5,] # only display some large MI values
```

```
# Visualization
semPaths(fit_mimic6, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE, rotation = 2)

##################################################################################
##################################################################################
model_mimic_full <-'
# Measurement model
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

# MIMIC
PolEf ~ hinctnta + agea + edlvdhu + fclcntr + gndr
'

fit_mimic_full <- sem(model_mimic_full,
                estimator = "ML",
                missing = 'direct',
                data = ess_df_selected
)

summary(fit_mimic_full,
      fit.measures = TRUE,
      standardized = TRUE
)

fitm_mimic_full <- fitMeasures(fit_mimic_full, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi",
"tli","rmsea"), output = "matrix")
fitm_mimic_full

## Modification Indexes
mi <- inspect(fit_mimic_full,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,] # only display some large MI
values
mi.sorted[1:5,] # only display some large MI values

# Visualization
semPaths(fit_mimic_full, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE, rotation = 2)

###################################################################################

data.frame(
        "w/lrscale" = round(fitm_mimic[,1],2),
        "w/hinctnta" = round(fitm_mimic_e[,1],2),
        "w/hinctnta" = round(fitm_mimic2[,1],2),
        "w/hinctnta + fclcntr" = round(fitm_mimic3[,1],2),
        "w/hinctnta + agea" = round(fitm_mimic4[,1],2),
        "w/hinctnta + agea + gndr" = round(fitm_mimic5[,1],2),
        "w/hinctnta + agea + eduhl" = round(fitm_mimic6[,1],2),
        "w/hinctnta + agea + eduhl + fclcntr + gndr" = round(fitm_mimic_full[,1],2)
```

```
)

#####################################################################################
#################
### MEDIATION  ###
#################
model_mediation <- '
## Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## SatCSA ##
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
stfedu ~~ stfhlth

## Direct effect ##
PolEf ~ c*hinctnta

## Mediator ##
SatCSA ~ a*hinctnta
PolEf ~ b*SatCSA

## Indirect effect (a*b) ##
ab := a*b
## Total effect ##
total := c + (a*b)
'

fit_mediation_fiml <- cfa(model_mediation, # model formula
               estimator = "ML",
               missing = 'direct',
               data = ess_df_selected
)

summary(fit_mediation_fiml,
      fit.measures = TRUE,
      standardized = TRUE
)


# Imputation
a.out <- amelia(ess_df_selected,  # original dataset with missing
            m = 15,    # number of m "completed" data sets
            seed = 22   # set the seed
)
# We can check each "completed" dataset against our original data
cbind(ess_df_selected$hinctnta, a.out$imputations$imp1$hinctnta)[c(75:85),]

# Fitting the model to multiple imputed data sets
fit_mediation_a <- semTools::runMI(
  model = model_mediation,        # model
```

```
 data = a.out$imputations, # list of imputed data sets
 fun = "sem",           # lavaan function
 estimator = "MLR"       # estimator
)

summary(fit_mediation_a,
    fit.measures=TRUE,
    standardized=TRUE)

### COMPARISON ###-------------------------------------------------------------
# let's compare the fit of the different models
model_fit <-  function(lavobject) {
 vars <- c("chisq", "df", "cfi", "tli", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper", "rmsea.pvalue",
"srmr")
 return(fitmeasures(lavobject)[vars] %>% data.frame() %>% round(2) %>% t())
}

table_fit_medi <-
 list(model_fit(fit_mediation_fiml),
    model_fit(fit_mediation_a)) %>%
 reduce(rbind)

rownames(table_fit_medi) <- c("FIML", "Amelia")

table_fit_medi

# Visualization
semPaths(fit_mediation_fiml, what = "std", optimizeLatRes = TRUE, layout = "tree", nCharNodes = 0,
intercepts = FALSE, fade = FALSE)

####################################################################################
model_mediation2 <- '
## Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## Trust ##
Trust =~ INSTT + IP
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc

## Direct effect ##
PolEf ~ c*hinctnta

## Mediator ##
Trust ~ a*hinctnta
PolEf ~ b*Trust
```

```
## Indirect effect (a*b) ##
ab := a*b
## Total effect ##
total := c + (a*b)
'

fit_mediation_fiml2 <- cfa(model_mediation2, # model formula
                 estimator = "ML",
                 missing = 'direct',
                 data = ess_df_selected
)

summary(fit_mediation_fiml2,
    fit.measures = TRUE,
    standardized = TRUE
)


# Imputation
a.out <- amelia(ess_df_selected,  # original dataset with missing
          m = 15,    # number of m "completed" data sets
          seed = 20  # set the seed
)
# We can check each "completed" dataset against our original data
cbind(ess_df_selected$hinctnta, a.out$imputations$imp1$hinctnta)[c(75:85),]

# Fitting the model to multiple imputed data sets
fit_mediation_a2 <- semTools::runMI(
 model = model_mediation2,      # model
 data = a.out$imputations, # list of imputed data sets
 fun = "sem",          # lavaan function
 estimator = "MLR"       # estimator
)

summary(fit_mediation_a2,
    fit.measures=TRUE,
    standardized=TRUE)

### COMPARISON ###-------------------------------------------------------------------
# let's compare the fit of the different models
model_fit <-  function(lavobject) {
 vars <- c("chisq", "df", "cfi", "tli", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper", "rmsea.pvalue",
"srmr")
 return(fitmeasures(lavobject)[vars] %>% data.frame() %>% round(2) %>% t())
}

table_fit_medi2 <-
 list(model_fit(fit_mediation_fiml2),
     model_fit(fit_mediation_a2)) %>%
 reduce(rbind)
```

```
rownames(table_fit_medi2) <- c("FIML", "Amelia")

table_fit_medi2

# Visualization
semPaths(fit_mediation_fiml2, what = "std", optimizeLatRes = TRUE, layout = "tree", nCharNodes =
0, intercepts = FALSE, fade = FALSE, rotation = 2)

#####################################################################################
model_mediation3 <- '
## Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## SatCSA ##
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
stfedu ~~ stfhlth

## Direct effect(s) ##
PolEf ~ c*agea + c1*edlvdhu + c2*hinctnta + c3*gndr + c4*fclcntr + c5*lrscale

## Mediator ##
# Path A
SatCSA ~ a*agea
SatCSA ~ a1*edlvdhu
SatCSA ~ a2*hinctnta
SatCSA ~ a3*gndr
SatCSA ~ a4*fclcntr
SatCSA ~ a5*lrscale

# Path B
PolEf ~ b*SatCSA

## Indirect effect (a*b) ##
ab_age := a*b
a1b_edl := a1*b
a2b_inco := a2*b
a3b_gndr := a3*b
a4b_fclcntr := a4*b
a5b_lrscale := a5*b


## Total effect ##
total_age := c + (a*b)
total1_edl := c1 + (a1*b)
total2_inco := c2 + (a2*b)
total3_gndr := c3 + (a3*b)
total4_fclcntr := c4 + (a4*b)
total5_lrscale := c5 + (a5*b)
'
```

```
fit_mediation3 <- cfa(model_mediation3,
            estimator = "ML",
            missing = 'direct',
            data = ess_df_selected
)

summary(fit_mediation3,
    fit.measures = TRUE,
    standardized = TRUE
)

# Global fit
fitMeasures(fit_mediation3, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_mediation3,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

# Visualization
semPaths(fit_mediation3, what = "std", optimizeLatRes = TRUE, layout = "tree", style = "ram",
nCharNodes = 0, intercepts = FALSE, fade = FALSE, rotation = 2)

##################################################################################
model_mediation4 <- '
## Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## Trust ##
Trust =~ INSTT + IP
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc

## Direct effect(s) ##
PolEf ~ c*agea + c1*edlvdhu + c2*hinctnta + c3*gndr + c4*fclcntr + c5*lrscale

## Mediator ##
# Path A
Trust ~ a*agea
Trust ~ a1*edlvdhu
Trust ~ a2*hinctnta
Trust ~ a3*gndr
Trust ~ a4*fclcntr
Trust ~ a5*lrscale

# Path B
PolEf ~ b*Trust
```

```
## Indirect effect (a*b) ##
ab_age := a*b
a1b_edl := a1*b
a2b_inco := a2*b
a3b_gndr := a3*b
a4b_fclcntr := a4*b
a5b_lrscale := a5*b


## Total effect ##
total_age := c + (a*b)
total1_edl := c1 + (a1*b)
total2_inco := c2 + (a2*b)
total3_gndr := c3 + (a3*b)
total4_fclcntr := c4 + (a4*b)
total5_lrscale := c5 + (a5*b)
'

fit_mediation4 <- cfa(model_mediation4,
                estimator = "ML",
                missing = 'direct',
                data = ess_df_selected
)

summary(fit_mediation4,
      fit.measures = TRUE,
      standardized = TRUE
)

fitMeasures(fit_mediation4, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")

# Visualization
semPaths(fit_mediation4, what = "std", optimizeLatRes = TRUE, sizeMan2 = 2, layout = "tree", style =
"Lisrel", nCharNodes = 0, intercepts = FALSE, fade = FALSE, rotation = 2)


# Global fit
fitMeasures(fit_mediation4, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output
= "matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_mediation4,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

####################################################################################
### Measurement equivalence ###
##############################
# Is Political efficacy measured equivalently across genders?
### Configural Invariance ###---------------------------------------------------
```

```
# Changing group to factor
ess_df_selected$gndr <- factor(ess_df_selected$gndr,
                levels = c("1", "2"),        # levels
                labels = c("Male", "Female")) # labels


fit_configural <- cfa(cfa_model_PolEf3,
                data = ess_df_selected,
                missing = 'direct',
                group = "gndr")


summary(fit_configural, fit.measures = TRUE, standardized=TRUE)

fitMeasures(fit_configural, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_configural,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

### Metric Invariance (also called "weak" invariance) ###-----------------------

fit_metric <- cfa(cfa_model_PolEf3,
             data = ess_df_selected,
             group = "gndr",
             missing = 'direct',
             group.equal = c("loadings")
)


summary(fit_metric, fit.measures = TRUE, standardized=TRUE)
# standardized loadings are set equal across groups

fitMeasures(fit_metric, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_metric,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

### Scalar Invariance (also called "strong" invariance) ###---------------------
# People who score zero on latent should score the same. Answer should not depend
# on group membership, only on teh latent factor.

fit_scalar <- cfa(cfa_model_PolEf3,
             data = ess_df_selected,
             group = "gndr",
             missing = 'direct',
             group.equal = c("loadings",
```

```
                  "intercepts")
)


summary(fit_scalar, fit.measures = TRUE, standardized=TRUE)
# The average female scores 2.195 on actrolg (because it's the value if latent equals zero,
# but since we set the latent mean zero for model identification purposes,
# this gives us the average for group 'Female')

#=> We can compare latent means starting from scalar => PolEf is lower for women 0 vs 0.171
# Is it a big diff? Can this be generalized for a bigger population = p-value sign., so yes (0.022).
# There is a diff between men and women in the latent mean.
# Strength = standardized solution = 0.122

fitMeasures(fit_scalar, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
# Local fit (Modification Indexes)
mi <- inspect(fit_scalar,"mi")
mi.sorted <- mi[order(-mi$mi),] # sort from high to low mi.sorted[1:5,]
mi.sorted[1:5,] # only display some large MI values

### Strict Invariance ###-----------------------------------------------------

fit_strict <- cfa(cfa_model_PolEf3,
          data = ess_df_selected,
          group = "gndr",
          missing = 'direct',
          group.equal = c("loadings",
                  "intercepts",
                  "residuals")
)


summary(fit_strict, fit.measures = TRUE, standardized=TRUE)

fitMeasures(fit_strict, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")

### Structural Invariance ###---------------------------------------------------

fit_structural <- cfa(cfa_model_PolEf3,
            data = ess_df_selected,
            group = "gndr",
            missing = 'direct',
            group.equal = c("loadings",
                    "intercepts",
                    "residuals",
                    "lv.variances",
                    "lv.covariances") # 1 latent var, no covariances
)
```

```
summary(fit_structural, fit.measures = TRUE, standardized=TRUE)
fitMeasures(fit_structural, c("logl","AIC", "BIC", "chisq", "df", "pvalue", "cfi", "tli","rmsea"), output =
"matrix")
semPaths(fit_structural, optimizeLatRes = TRUE, layout = "tree", style = "ram", nCharNodes = 0,
intercepts = FALSE, fade = FALSE)

### Evaluating measurement invariance ###--------------------------------------

model_fit <-  function(lavobject) {
  vars <- c("df", "cfi", "tli", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper", "rmsea.pvalue", "srmr")
  return(fitmeasures(lavobject)[vars] %>% data.frame() %>% round(2) %>% t())
}

table_fit <-
  list(model_fit(fit_configural),
       model_fit(fit_metric),
       model_fit(fit_scalar),
       model_fit(fit_strict),
       model_fit(fit_structural)) %>%
  reduce(rbind)


rownames(table_fit) <- c("Configural", "Metric", "Scalar","Strict","Structural")

table_fit

# Comparing nested models with Anova (based on the chi square difference test)

table_anova <- list(anova(fit_configural, fit_metric),
                anova(fit_metric, fit_scalar),
                anova(fit_scalar, fit_strict),
                anova(fit_strict, fit_structural)) %>%
  reduce(rbind) %>%
  .[-c(3, 5, 7),]

table_anova
# Invariance is achieved if there is a non-significant chi-square change
# If p-value non-significant no distance between two models => choose more parsimonious.
# So far we have metric invariance (massive n => small differences show up too).

# Anova uses X^2 => sensitive to departures from normality and large sample sizes => detects small
deviations
# Other fit indices indicate that we do get a reasonable fit.

# More Robust comparison using Bootstrap
# Using the bootstrapLavaan() function to obtain bootstrapped estimates of the model parameters
# boot_configural <- bootstrapLavaan(fit_configural, R = 1000)
# boot_metric <- bootstrapLavaan(fit_metric, R = 100)
boot_scalar <- bootstrapLavaan(fit_scalar, R = 100)
boot_strict <- bootstrapLavaan(fit_strict, R = 100)
```

```
boot_structural <- bootstrapLavaan(fit_structural, R = 100)

# Compare the bootstrapped estimates
summary(boot_scalar, fit.measures = TRUE)
summary(boot_strict, fit.measures = TRUE)
summary(boot_structural, fit.measures = TRUE)

####################################################################################
### Partial Invariance ###
####################################################################################
# Can we achieve partial scalar invariance?

# Effects of releasing equality constraints across groups:
lavTestScore(fit_scalar) # First output multivariate score test (i.e. Lagrange multiplier test).
# It indicates whether freeing all equality constraints represents an improvement in fit
# over the base model (global misfit). In this case we reject the H0.
# 2nd part univariate score test => p17. == .p36 has largest X2 diff.
# It gives MI for each constrained parameter.

# psppsgv => relates to group 2 (Females)
# ustart - value fixed at that value
parTable(fit_scalar)
# the intercepts for psppsgv in the two different blocks of the model
# appear to be significantly different from each other.
# Man and women answer different at level zero latent factor. Gender influences how they respond.

fit_scalar_psppsgv <- cfa(cfa_model_PolEf3,
                data = ess_df_selected,
                group = "gndr",
                group.equal = c("loadings",
                          "intercepts"),
                missing = 'direct',
                group.partial = c(psppsgv~1)

)

summary(fit_scalar_psppsgv, fit.measures = TRUE, standardized=TRUE)
anova(fit_metric, fit_scalar_psppsgv)
#--------------------------------------------------------------------------------
lavTestScore(fit_scalar_psppsgv)
parTable(fit_scalar_psppsgv)

fit_scalar_psppsgv_ptcpplt <- cfa(cfa_model_PolEf3,
                data = ess_df_selected,
                group = "gndr",
                group.equal = c("loadings",
                          "intercepts"),
                missing = 'direct',
                group.partial = c(psppsgv~1, ptcpplt ~1)

)
```

```
summary(fit_scalar_psppsgv_ptcpplt, fit.measures = TRUE, standardized=TRUE)


table_fit <-
  list(model_fit(fit_metric),
       model_fit(fit_scalar),
       model_fit(fit_scalar_psppsgv),
       model_fit(fit_scalar_psppsgv_ptcpplt),
       model_fit(fit_scalar_psppsgv_ptcpplt_psppipl)) %>%
  reduce(rbind)


rownames(table_fit) <- c("Metric", "Scalar", "Plus_psppsgv","Plus_ptcpplt","Plus_psppipl")

table_fit

table_anova2 <-
  list(anova(fit_configural, fit_metric),
       anova(fit_metric, fit_scalar),
       anova(fit_metric, fit_scalar_psppsgv),
       anova(fit_metric, fit_scalar_psppsgv_ptcpplt)) %>%
  reduce(rbind) %>%
  .[-c(3, 5, 7),]
table_anova2

#-----------------------------------------------------------------------------
lavTestScore(fit_scalar_psppsgv_ptcpplt)
parTable(fit_scalar_psppsgv_ptcpplt)

fit_scalar_psppsgv_ptcpplt_psppipl <- cfa(cfa_model_PolEf3,
                         data = ess_df_selected,
                         group = "gndr",
                         group.equal = c("loadings",
                                    "intercepts"),
                         missing = 'direct',
                         group.partial = c(psppsgv~1, ptcpplt ~1, psppipl ~1)

)

summary(fit_scalar_psppsgv_ptcpplt_psppipl, fit.measures = TRUE, standardized=TRUE)

table_anova3 <-
  list(anova(fit_configural, fit_metric),
       anova(fit_metric, fit_scalar),
       anova(fit_metric, fit_scalar_psppsgv),
       anova(fit_metric, fit_scalar_psppsgv_ptcpplt),
       anova(fit_metric, fit_scalar_psppsgv_ptcpplt_psppipl)) %>%
  reduce(rbind) %>%
  .[-c(3, 5, 7, 9),]

table_anova3 # partial scalar invariance reached
```

```
######################################################################################
### Multi-group SEM ###
######################################################################################

# We include structural part too. (Can be anything, MIMIC, mediation, etc.)
# Group specific direct and indirect effects
# We test regression path invariance.

# Group.equal ="loadings" => Metric invariance => We want to compare effects size across groups =>
# => Group specific direct and indirect effects => We need metric invariance.

# Unconstrained model:
model_mediation_mg <- '
# Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## SatCSA ##
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
stfedu ~~ stfhlth

## Direct effect ##
PolEf ~ c("c1", "c2")*hinctnta

## Mediator ##
SatCSA ~ c("a1", "a2")*hinctnta
PolEf ~ c("b1", "b2")*SatCSA

## Indirect effect (a*b) ##
a1b1 := a1*b1
a2b2 := a2*b2

## Total effect c + (a*b) ##
total1 := c1 + (a1*b1)
total2 := c2 + (a2*b2)
'

fit_mediation_mg <- cfa(model_mediation_mg,
              data = ess_df_selected,
              estimator = "ML",
              missing = 'direct',
              group = "gndr",
              group.equal = c("loadings")  # equal loadings => metric invariance

)

summary(fit_mediation_mg, fit.measures = TRUE, standardized=TRUE)
# 56 degrees of freedom. Poor fit according to x^2, but good according to alternative indices.
# Factor loadings equal across group - "Estimate"
# Regression effects not equal, because we gave them different names.
```

```
#------------------------------------------------------------------------------
# Fixing the loadings and the path coefficients = regression effects equal across groups.
model_mediation_mg_cons <- '
# Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## SatCSA ##
SatCSA =~ stfeco + stfgov + stfdem + stfedu + stfhlth
stfedu ~~ stfhlth

## Direct effect ##
PolEf ~ c("c1", "c1")*hinctnta

## Mediator ##
SatCSA ~ c("a1", "a1")*hinctnta
PolEf ~ c("b1", "b1")*SatCSA

## Indirect effect (a*b) ##
a1b1 := a1*b1

## Total effect c + (a*b) ##
total1 := c1 + (a1*b1)
'

fit_mediation_mg_cons <- cfa(model_mediation_mg_cons,
                    data = ess_df_selected,
                    estimator = "ML",
                    group = "gndr",
                    missing = 'direct',
                    group.equal = c("loadings")

)

summary(fit_mediation_mg_cons, fit.measures = TRUE, standardized=TRUE)

# Anova comparison of the two model: (The restricted model will never be a better fit, never have a
lower X2.
# H0: They perform equally well (We chose the more parsimonious). HA: They don't => We need to
settle for the less restrictive model (less parsimonious). )

anova(fit_mediation_mg, fit_mediation_mg_cons)
# The insignificant P-value implies that the unconstrained and the constrained models are not
statistically significantly different.
# In this case, we go for the more parsimonious=constrained model.
# This means that the path coefficients vary very little by group.
# and we can analyse the pooled data in a single global model.

#####################################################################################
### TRUST VS POLEF ###
```

```
# Unconstrained model
model_mediation_mg_full <- '
## Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## Trust ##
Trust =~ INSTT + IP
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc

## Direct effect ##
PolEf ~ c("c_edu_1", "c_edu_2")*edlvdhu
PolEf ~ c("c_inc_1", "c_inc_2")*hinctnta
PolEf~ c("c_fclcntr_1", "c_fclcntr_2")*fclcntr
PolEf ~ c("c_po_1", "c_po_2")*lrscale

## Mediator ##
# Path A
Trust ~ c("a_edu_1", "a_edu_2")*edlvdhu
Trust ~ c("a_inc_1", "a_inc_2")*hinctnta
Trust~ c("a_fclcntr_1", "a_fclcntr_2")*fclcntr
Trust ~ c("a_po_1", "a_po_2")*lrscale

# Path B
PolEf ~ c("b1", "b2")*Trust

## Indirect effect (a*b) ##
# F
ab_edu_F := a_edu_1*b1
ab_inc_F := a_inc_1*b1
ab_fclcntr_F := a_fclcntr_1*b1
ab_po_F := a_po_1*b1

# M
ab_edu_M := a_edu_2*b2
ab_inc_M := a_inc_2*b2
ab_fclcntr_M := a_fclcntr_2*b2
ab_po_M := a_po_2*b2

## Total effect c + (a*b) ##
# F
total_edu_F := c_edu_1 + (a_edu_1*b1)
total_inc_F := c_inc_1 + (a_inc_1*b1)
total_fclcntr_F := c_fclcntr_1 + (a_fclcntr_1*b1)
total_po_F := c_po_1 + (a_po_1*b1)
```

```
# M
total_edu_M := c_edu_2 + (a_edu_2*b2)
total_inc_M := c_inc_2 + (a_inc_2*b2)
total_fclcntr_M := c_fclcntr_2 + (a_fclcntr_2*b2)
total_po_M := c_po_2 + (a_po_2*b2)
'

fit_mediation_mg <- cfa(model_mediation_mg,
                data = ess_df_selected,
                estimator = "ML",
                group = "gndr",
                missing = 'direct',
                group.equal = c("loadings")
)

summary(fit_mediation_mg,
      standardized=TRUE,
      fit.measures = TRUE
)


# Constrained model

model_mediation_mg_full_cons <- '
## Political efficacy ##
PolEf =~ actrolg + cptppol + psppipl + psppsgv + ptcpplt
actrolg ~~ cptppol

## Trust ##
Trust =~ INSTT + IP
INSTT =~ trstlgl + trstplc + trstplt + trstep + trstun + trstprt + trstprl
IP =~ ppltrst + pplfair + pplhlp
trstplt ~~ trstprt
trstep ~~  trstun
trstlgl ~~ trstplc

## Direct effect ##
PolEf ~ c("c_edu_1", "c_edu_1")*edlvdhu
PolEf ~ c("c_inc_1", "c_inc_1")*hinctnta
PolEf~ c("c_fclcntr_1", "c_fclcntr_1")*fclcntr
PolEf ~ c("c_po_1", "c_po_1")*lrscale

## Mediator ##
# Path A
Trust ~ c("a_edu_1", "a_edu_1")*edlvdhu
Trust ~ c("a_inc_1", "a_inc_1")*hinctnta
Trust~ c("a_fclcntr_1", "a_fclcntr_1")*fclcntr
Trust ~ c("a_po_1", "a_po_1")*lrscale

# Path B
PolEf ~ c("b1", "b1")*Trust
```

```
## Indirect effect (a*b) ##
ab_edu_F := a_edu_1*b1
ab_inc_F := a_inc_1*b1
ab_fclcntr_F := a_fclcntr_1*b1
ab_po_F := a_po_1*b1


## Total effect c + (a*b) ##
total_edu_F := c_edu_1 + (a_edu_1*b1)
total_inc_F := c_inc_1 + (a_inc_1*b1)
total_fclcntr_F := c_fclcntr_1 + (a_fclcntr_1*b1)
total_po_F := c_po_1 + (a_po_1*b1)
'


fit_mediation_mg_cons <- cfa(model_mediation_mg_cons,
            data = ess_df_selected,
            estimator = "ML",
            group = "gndr",
            missing = 'direct',
            group.equal = c("loadings")
)

summary(fit_mediation_mg_cons,
    standardized=TRUE,
    fit.measures = TRUE
)


#### COMPARISON ####
anova(fit_mediation_mg, fit_mediation_mg_cons)

# Total and indirect effect and paths do not differ significantly across groups.
# The insignificant P-value implies that the unconstrained and the constrained models are not
statistically significantly different.
# In this case, we go for the more parsimonious=constrained model.
# This means that the path coefficients vary very little by group.
# and we can analyse the pooled data in a single global model.
# Factor loadings, regression coefficients equal across groups.

table_fit <-
  list(model_fit(fit_mediation_mg),
      model_fit(fit_mediation_mg_cons)) %>%
  reduce(rbind)

rownames(table_fit) <- c("Unconstrained", "Constrained")

table_fit
```

```
semPaths(fit_mediation_mg, what = "std", optimizeLatRes = TRUE, layout = "spring", style = "lisrel2",
nCharNodes = 0, intercepts = FALSE, fade = FALSE)

# Unloading packages ------------------------------------------------------------
detach("package:rio", unload = T)
detach("package:dplyr", unload = T)
detach("package:psych", unload = T)
detach("package:stringr", unload = T)
detach("package:purrr", unload = T)
detach("package:lavaan", unload = T)
detach("package:MVN", unload = T)
detach("package:Amelia", unload = T)
detach("package:mice", unload = T)
detach("package:semTools", unload = T)
detach("package:tidySEM", unload = T)
detach("package:ggplot2", unload = T)
detach("package:semPlot", unload = T)
detach("package:patchwork", unload = T)
detach("package:conflicted", unload = T)
detach("package:GGally", unload = T)
detach("package:Hmisc", unload = T)
detach("package:naniar", unload = T)
```