

# Calculation and analysis of variables

## Socioeconomic and Gender Disparities: A Multi-Country Study

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## 1 Presentation

This is the calculation and analysis of variables code of the data for the project Socioeconomic and Gender Disparities: A Multi-Country Study. The data used is `db_proc.RData`

## 2 Libraries

First, we load the necessary libraries. In this case, we use `pacman::p_load` to load and call libraries in one move.

```
if (! require("pacman")) install.packages("pacman")

pacman::p_load(tidyverse,
               haven,
               sjmisc,
               sjPlot,
               here,
               lavaan,
               psych,
               rstatix,
               ggdist,
               patchwork,
               sjlabelled,
```

```
semTools,
gtools,
RColorBrewer,
skimr)

options(scipen=999)
rm(list = ls())
```

### 3 Data

We load the database from the local path. Modify this later.

```
load(file = here("output/data/db_proc.RData"))

glimpse(db_proc)
```

```
Rows: 4,209
Columns: 212
$ ID <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 1~
$ StartDate <dtm> 2024-04-28 11:11:20, 2024-04-28 11:12:34, 2~
$ EndDate <dtm> 2024-04-28 11:30:12, 2024-04-28 11:31:15, 2~
$ IPAddress <chr> "90.167.243.1", "83.58.124.179", "79.152.186~
$ Duration__in_seconds <dbl> 1132, 1120, 1192, 1410, 1328, 645, 933, 886,~
$ RecordedDate <dtm> 2024-04-28 11:30:12, 2024-04-28 11:31:16, 2~
$ ResponseId <chr> "R_1eqka09S3bZXYTp", "R_42oDc55cfSucfrX", "R~
$ LocationLatitude <chr> "41.6362", "41.3891", "41.4287", "41.5453", ~
$ LocationLongitude <chr> "-4.7435", "2.1606", "2.2164", "2.4414", "-5~
$ eco_in_1 <dbl+lbl> 6, 6, 7, 6, 6, 4, 4, 3, 6, 3, 7, 7, 5, 5~
$ eco_in_2 <dbl+lbl> 6, 6, 7, 6, 6, 4, 5, 4, 3, 4, 1, 6, 5, 6~
$ eco_in_3 <dbl+lbl> 7, 6, 7, 6, 6, 4, 2, 3, 5, 3, 5, 4, 6, 6~
$ jus_ine <dbl+lbl> 1, 2, 1, 1, 2, 5, 1, 1, 2, 1, 2, 5, 3, 4~
$ co_eco <dbl+lbl> 7, 7, 6, 4, 5, 3, 6, 6, 3, 2, 1, 4, 5, 5~
$ pp_pw_1 <dbl+lbl> 7, 4, 6, 2, 5, 5, 3, 3, 2, 5, 7, 5, 5, 5~
$ pp_pw_2 <dbl+lbl> 7, 5, 6, 3, 6, 5, 5, 7, 2, 5, 2, 5, 5, 5~
$ pp_pw_3 <dbl+lbl> 7, 6, 7, 2, 5, 3, 3, 5, 2, 4, 2, 4, 5, 5~
$ pp_pw_4 <dbl+lbl> 7, 4, 4, 1, 5, 5, 3, 5, 2, 5, 4, 3, 5, 5~
$ cc_pw_1 <dbl+lbl> 5, 4, 6, 3, 6, 4, 5, 6, 5, 4, 4, 6, 6, 4~
$ cc_pw_2 <dbl+lbl> 4, 2, 4, 2, 5, 4, 4, 4, 2, 4, 2, 4, 4, 4~
```

\$ cc_pw_3	<dbl+lbl> 4, 3, 6, 4, 6, 4, 4, 4, 2, 5, 7, 5, 6, 4~
\$ cc_pw_4	<dbl+lbl> 3, 5, 5, 3, 6, 4, 5, 5, 4, 4, 7, 6, 6, 4~
\$ hc_pw_1	<dbl+lbl> 1, 1, 1, 1, 1, 4, 2, 2, 1, 3, 1, 2, 4, 4~
\$ hc_pw_2	<dbl+lbl> 2, 1, 2, 3, 3, 4, 2, 3, 1, 6, 1, 2, 5, 4~
\$ hc_pw_3	<dbl+lbl> 1, 1, 4, 2, 2, 4, 1, 2, 1, 3, 1, 2, 2, 4~
\$ hc_pw_4	<dbl+lbl> 2, 2, 2, 1, 2, 3, 4, 2, 1, 4, 1, 2, 5, 4~
\$ pp_pm_1	<dbl+lbl> 6, 5, 6, 4, 5, 5, 3, 6, 2, 5, 7, 5, 6, 5~
\$ pp_pm_2	<dbl+lbl> 7, 5, 7, 2, 6, 3, 2, 6, 2, 5, 5, 5, 4, 5~
\$ pp_pm_3	<dbl+lbl> 7, 6, 6, 3, 5, 3, 3, 6, 2, 5, 7, 3, 5, 5~
\$ pp_pm_4	<dbl+lbl> 7, 4, 6, 3, 5, 3, 3, 5, 2, 4, 7, 4, 6, 5~
\$ cc_pm_1	<dbl+lbl> 7, 4, 4, 3, 5, 4, 5, 3, 5, 3, 2, 5, 5, 4~
\$ cc_pm_2	<dbl+lbl> 4, 2, 1, 1, 4, 4, 3, 4, 2, 2, 2, 4, 4, 4~
\$ cc_pm_3	<dbl+lbl> 4, 3, 2, 3, 4, 4, 4, 4, 2, 3, 1, 4, 6, 4~
\$ cc_pm_4	<dbl+lbl> 3, 5, 5, 2, 4, 5, 4, 4, 2, 3, 2, 6, 3, 4~
\$ hc_pm_1	<dbl+lbl> 3, 1, 4, 3, 3, 3, 2, 4, 4, 4, 7, 3, 5, 4~
\$ hc_pm_2	<dbl+lbl> 3, 1, 5, 3, 3, 3, 2, 3, 2, 4, 7, 3, 5, 4~
\$ hc_pm_3	<dbl+lbl> 2, 1, 3, 1, 2, 4, 2, 3, 2, 5, 7, 3, 6, 4~
\$ hc_pm_4	<dbl+lbl> 3, 2, 4, 2, 5, 4, 2, 4, 1, 5, 7, 3, 5, 4~
\$ gen_in_1	<dbl+lbl> 6, 7, 6, 7, 7, 3, 7, 7, 6, 5, 4, 6, 7, 4~
\$ gen_in_2	<dbl+lbl> 6, 7, 6, 5, 7, 3, 5, 6, 1, 6, 7, 7, 7, 5~
\$ gen_in_3	<dbl+lbl> 5, 7, 5, 7, 4, 3, 4, 7, 6, 6, 7, 5, 6, 4~
\$ gen_in_4	<dbl+lbl> 3, 6, 5, 6, 6, 3, 5, 5, 5, 6, 7, 5, 3, 5~
\$ gen_in_5	<dbl+lbl> 4, 6, 3, 5, 7, 3, 7, 4, 6, 5, 6, 5, 3, 4~
\$ gen_in_6	<dbl+lbl> 6, 7, 5, 6, 4, 2, 5, 7, 6, 6, 7, 5, 7, 4~
\$ ps_m_1	<dbl+lbl> 7, 2, 4, 1, 3, 3, 3, 4, 1, 4, 1, 7, 6, 4~
\$ ps_m_2	<dbl+lbl> 6, 1, 2, 5, 1, 4, 1, 4, 1, 1, 1, 5, 4, 4~
\$ ps_m_3	<dbl+lbl> 6, 2, 4, 3, 4, 2, 4, 4, 1, 4, 7, 3, 6, 4~
\$ hs_m_1	<dbl+lbl> 1, 1, 2, 1, 2, 3, 2, 2, 1, 3, 1, 2, 4, 4~
\$ hs_m_2	<dbl+lbl> 1, 1, 5, 1, 3, 3, 1, 2, 1, 2, 1, 2, 5, 4~
\$ hs_m_3	<dbl+lbl> 1, 2, 1, 1, 2, 4, 1, 2, 1, 3, 1, 3, 5, 4~
\$ shif_1	<dbl+lbl> 1, 1, 2, 2, 2, 6, 1, 1, 1, 2, 1, 5, 5, 4~
\$ shif_2	<dbl+lbl> 1, 1, 2, 1, 2, 5, 1, 1, 1, 2, 1, 4, 2, 4~
\$ shif_3	<dbl+lbl> 1, 1, 1, 4, 2, 3, 1, 1, 1, 2, 3, 5, 3, 4~
\$ femi	<dbl+lbl> 7, 7, 3, 5, 5, 1, 7, 5, 6, 2, 4, 2, 1, 4~
\$ co_gen	<dbl+lbl> 7, 7, 3, 4, 5, 3, 6, 5, 2, 2, 1, 4, 4, 4~
\$ jus_gen	<dbl+lbl> 1, 2, 1, 2, 3, 3, 3, 1, 1, 1, 1, 5, 3, 4~
\$ gen_compe	<dbl+lbl> 4, 6, 5, 5, 4, 4, 1, 4, 4, 4, 1, 5, 5, 4~
\$ ge_ra_wo	<dbl> 70, 70, 60, 60, 40, 20, 50, 20, 27, 60, 85, ~
\$ ge_ra_me	<dbl> 30, 30, 40, 40, 60, 80, 50, 80, 73, 40, 15, ~
\$ quan_pw	<dbl+lbl> 1, 4, 5, 3, 5, 3, 3, 2, 1, 2, 1, 3, 2, 2~
\$ quan_pm	<dbl+lbl> 1, 4, 5, 3, 5, 4, 3, 3, 1, 2, 1, 3, 2, 2~

\$ quan_rw	<dbl+lbl> 1, 5, 5, 4, 7, 3, 2, 2, 7, 1, 5, 3, 4, 2~
\$ quan_rm	<dbl+lbl> 1, 5, 5, 4, 7, 4, 2, 2, 7, 1, 5, 2, 4, 2~
\$ fri_pw	<dbl+lbl> 1, 1, 2, 3, 3, 4, 2, 1, 1, 3, 1, 2, 1, 1~
\$ fri_pm	<dbl+lbl> 1, 1, 1, 2, 3, 4, 2, 1, 1, 3, 1, 1, 1, 1~
\$ fri_rw	<dbl+lbl> 2, 4, 6, 4, 6, 4, 1, 1, 5, 1, 6, 4, 1, 1~
\$ fri_rm	<dbl+lbl> 2, 5, 6, 3, 6, 4, 1, 1, 5, 1, 7, 4, 1, 1~
\$ qual_pw	<dbl+lbl> 4, 5, 4, 4, 6, 4, 3, 3, 2, 4, 4, 3, 2, 4~
\$ qual_pm	<dbl+lbl> 4, 5, 3, 4, 4, 4, 3, 3, 2, 4, 4, 3, 2, 4~
\$ qual_rw	<dbl+lbl> 2, 5, 6, 3, 5, 4, 3, 4, 4, 4, 7, 4, 3, 4~
\$ qual_rm	<dbl+lbl> 2, 5, 5, 3, 5, 4, 3, 4, 4, 4, 7, 4, 3, 4~
\$ mobi_up_1	<dbl+lbl> 4, 3, 3, 5, 2, 3, 1, 3, 1, 4, 5, 5, 6, 5~
\$ mobi_up_2	<dbl+lbl> 4, 4, 5, 3, 3, 4, 1, 3, 1, 2, 4, 5, 5, 5~
\$ mobi_up_3	<dbl+lbl> 5, 3, 1, 6, 2, 4, 1, 4, 1, 3, 3, 5, 5, 4~
\$ mobi_down_1	<dbl+lbl> 5, 6, 6, 6, 5, 4, 5, 5, 6, 4, 5, 3, 2, 4~
\$ mobi_down_2	<dbl+lbl> 5, 4, 5, 2, 4, 3, 4, 4, 5, 4, 1, 3, 2, 3~
\$ mobi_down_3	<dbl+lbl> 4, 5, 3, 3, 5, 4, 3, 4, 6, 4, 1, 3, 2, 3~
\$ condi_gender	<dbl+lbl> 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0~
\$ condi_class	<dbl+lbl> 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1~
\$ mor_1	<dbl+lbl> 1, 4, 3, 6, 3, 4, 2, 3, 3, 5, 5, 2, 5, 4~
\$ mor_2	<dbl+lbl> 2, 3, 4, 5, 2, 5, 3, 4, 4, 4, 5, 3, 4, 4~
\$ mor_3	<dbl+lbl> 2, 3, 3, 4, 3, 4, 2, 3, 4, 3, 6, 3, 2, 4~
\$ inm_1	<dbl+lbl> 7, 5, 6, 3, 6, 4, 2, 3, 3, 4, 1, 7, 4, 4~
\$ inm_2	<dbl+lbl> 6, 4, 4, 2, 3, 3, 2, 3, 5, 2, 1, 6, 3, 4~
\$ inm_3	<dbl+lbl> 5, 5, 4, 1, 6, 5, 2, 4, 4, 4, 2, 5, 5, 4~
\$ war_1	<dbl+lbl> 4, 4, 2, 4, 5, 4, 5, 4, 5, 5, 5, 3, 5, 4~
\$ war_2	<dbl+lbl> 2, 3, 4, 5, 4, 3, 3, 4, 4, 4, 5, 3, 4, 4~
\$ war_3	<dbl+lbl> 4, 4, 2, 6, 5, 3, 5, 5, 4, 5, 5, 3, 4, 4~
\$ com_1	<dbl+lbl> 7, 6, 4, 5, 5, 5, 3, 4, 4, 3, 6, 5, 3, 5~
\$ com_2	<dbl+lbl> 6, 6, 5, 5, 5, 5, 3, 5, 5, 4, 6, 5, 2, 5~
\$ com_3	<dbl+lbl> 5, 5, 3, 5, 5, 6, 3, 4, 5, 5, 6, 4, 3, 5~
\$ ph_1	<dbl+lbl> 4, 1, 2, 1, 6, 2, 1, 1, 5, 1, 1, 6, 3, 2~
\$ ph_2	<dbl+lbl> 4, 1, 6, 1, 6, 2, 1, 1, 5, 4, 1, 5, 4, 2~
\$ ah_1	<dbl+lbl> 2, 2, 1, 1, 5, 2, 2, 1, 1, 1, 1, 1, 2, 2~
\$ ah_2	<dbl+lbl> 2, 1, 2, 1, 5, 2, 2, 1, 1, 1, 1, 1, 1, 2~
\$ pf_1	<dbl+lbl> 4, 4, 5, 5, 3, 4, 2, 7, 3, 5, 7, 5, 5, 4~
\$ pf_2	<dbl+lbl> 1, 5, 1, 4, 3, 5, 5, 2, 5, 2, 4, 3, 4, 4~
\$ af_1	<dbl+lbl> 1, 4, 1, 5, 3, 3, 3, 7, 2, 2, 7, 2, 3, 4~
\$ af_2	<dbl+lbl> 1, 3, 2, 7, 4, 4, 2, 7, 4, 5, 4, 4, 5, 4~
\$ ad_1	<dbl+lbl> 1, 4, 2, 5, 3, 5, 1, 5, 2, 3, 2, 3, 4, 4~
\$ ad_2	<dbl+lbl> 4, 4, 5, 6, 2, 5, 3, 7, 2, 6, 7, 4, 6, 4~
\$ co_1	<dbl+lbl> 2, 1, 1, 1, 6, 2, 4, 1, 5, 1, 1, 1, 3, 2~

\$ co_2	<dbl+lbl> 2, 2, 2, 1, 6, 2, 2, 1, 4, 1, 1, 3, 4, 2~
\$ en_1	<dbl+lbl> 1, 1, 1, 2, 2, 2, 4, 1, 3, 1, 1, 1, 1, 2~
\$ en_2	<dbl+lbl> 1, 1, 1, 1, 2, 2, 4, 1, 4, 1, 1, 1, 1, 2~
\$ pi_1	<dbl+lbl> 1, 1, 6, 4, 5, 1, 2, 6, 4, 3, 6, 6, 6, 2~
\$ pi_2	<dbl+lbl> 1, 1, 6, 3, 1, 2, 1, 7, 2, 4, 7, 5, 5, 2~
\$ sk_1	<dbl+lbl> 7, 6, 6, 7, 6, 2, 7, 6, 4, 5, 7, 5, 3, 4~
\$ sk_2	<dbl+lbl> 7, 7, 6, 5, 7, 2, 7, 7, 5, 6, 7, 3, 5, 4~
\$ sk_3	<dbl+lbl> 7, 7, 7, 7, 7, 2, 7, 5, 4, 6, 7, 7, 5, 4~
\$ ex_po_1	<dbl+lbl> NA, NA, 5, 7, NA, NA, NA, 7, NA, 7, ~
\$ ex_po_2	<dbl+lbl> NA, NA, 6, 5, NA, NA, NA, 6, NA, 7, ~
\$ in_po_1	<dbl+lbl> NA, NA, 4, 2, NA, NA, NA, 4, NA, 4, ~
\$ in_po_2	<dbl+lbl> NA, NA, 2, 1, NA, NA, NA, 5, NA, 5, ~
\$ ex_we_1	<dbl+lbl> 7, 7, NA, NA, 7, 4, 7, NA, 6, NA, ~
\$ ex_we_2	<dbl+lbl> 7, 7, NA, NA, 7, 4, 7, NA, 6, NA, ~
\$ in_we_1	<dbl+lbl> 7, 5, NA, NA, 3, 5, 3, NA, 2, NA, ~
\$ in_we_2	<dbl+lbl> 3, 5, NA, NA, 3, 5, 2, NA, 1, NA, ~
\$ carin_control_1	<dbl+lbl> NA, NA, 4, 7, NA, NA, NA, 2, NA, 4, ~
\$ carin_control_2	<dbl+lbl> NA, NA, 3, 1, NA, NA, NA, 2, NA, 4, ~
\$ carin_attitude_1	<dbl+lbl> NA, NA, 5, 1, NA, NA, NA, 4, NA, 2, ~
\$ carin_attitude_2	<dbl+lbl> NA, NA, 7, 1, NA, NA, NA, 2, NA, 3, ~
\$ carin_reciprocity_1	<dbl+lbl> NA, NA, 3, 4, NA, NA, NA, 3, NA, 3, ~
\$ carin_reciprocity_2	<dbl+lbl> NA, NA, 5, 1, NA, NA, NA, 2, NA, 4, ~
\$ carin_identity_1	<dbl+lbl> NA, NA, 3, 1, NA, NA, NA, 1, NA, 1, ~
\$ carin_identity_2	<dbl+lbl> NA, NA, 1, 2, NA, NA, NA, 5, NA, 1, ~
\$ carin_need_1	<dbl+lbl> NA, NA, 6, 1, NA, NA, NA, 1, NA, 5, ~
\$ carin_need_2	<dbl+lbl> NA, NA, 5, 1, NA, NA, NA, 1, NA, 5, ~
\$ greedy_1	<dbl+lbl> 7, 6, NA, NA, 7, 2, 3, NA, 7, NA, ~
\$ greedy_2	<dbl+lbl> 7, 6, NA, NA, 7, 3, 4, NA, 6, NA, ~
\$ greedy_3	<dbl+lbl> 7, 6, NA, NA, 7, 3, 4, NA, 5, NA, ~
\$ punish_1	<dbl+lbl> 7, 7, NA, NA, 7, 2, 6, NA, 7, NA, ~
\$ punish_2	<dbl+lbl> 7, 7, NA, NA, 7, 2, 7, NA, 7, NA, ~
\$ punish_3	<dbl+lbl> 7, 7, NA, NA, 7, 2, 7, NA, 7, NA, ~
\$ asc_pw	<dbl> 50, 61, 69, 53, 80, 51, 50, 73, 51, 65, 51, ~
\$ asc_pm	<dbl> 50, 61, 61, 54, 70, 47, 51, 39, 51, 65, 30, ~
\$ asc_rw	<dbl> 50, 76, 40, 48, 80, 65, 51, 73, 51, 15, 80, ~
\$ asc_rm	<dbl> 50, 75, 61, 51, 70, 64, 51, 58, 51, 15, 70, ~
\$ wel_abu_1	<dbl+lbl> 1, 1, 3, 1, 2, 2, 3, 4, 1, 4, 2, 3, 3, 5~
\$ wel_abu_2	<dbl+lbl> 1, 1, 2, 1, 2, 2, 3, 2, 1, 2, 2, 4, 3, 5~
\$ wel_pa_1	<dbl+lbl> 7, 2, 7, 1, 6, 2, 3, 6, 5, 7, 7, 5, 6, 5~
\$ wel_pa_2	<dbl+lbl> 7, 2, 7, 1, 6, 2, 5, 6, 4, 6, 7, 7, 5, 5~
\$ wel_ho_1	<dbl+lbl> 1, 1, 1, 1, 2, 2, 2, 3, 1, 5, 1, 1, 2, 5~

\$ wel_ho_2	<dbl+lbl> 1, 1, 1, 1, 2, 2, 4, 4, 1, 6, 1, 4, 2, 5~
\$ pro_pw	<dbl+lbl> 4, 2, 3, 1, 2, 3, 3, 2, 1, 2, 1, 2, 5, 4~
\$ pro_rw	<dbl+lbl> 4, 2, 6, 1, 5, 4, 3, 4, 1, 6, 7, 5, 6, 4~
\$ ris_pw	<dbl+lbl> 6, 2, 6, 1, 6, 4, 3, 3, 4, 4, 7, 6, 6, 4~
\$ ris_rw	<dbl+lbl> 3, 1, 5, 1, 4, 4, 3, 3, 5, 5, 5, 4, 2, 4~
\$ pre_pw	<dbl+lbl> 6, 3, 6, 3, 6, 4, 4, 3, 5, 5, 7, 4, 6, 5~
\$ pre_rw	<dbl+lbl> 3, 1, 4, 3, 2, 4, 2, 3, 3, 2, 2, 5, 1, 2~
\$ redi_1	<dbl+lbl> 7, 7, 7, 5, 7, 4, 7, 7, 6, 7, 6, 5, 6, 5~
\$ redi_2	<dbl+lbl> 7, 7, 6, 1, 7, 3, 7, 7, 7, 7, 1, 6, 7, 6~
\$ effec_pw_1	<dbl+lbl> 1, 1, 5, 1, 3, 3, 2, 2, 2, 3, 2, 4, 2, 4~
\$ effec_pw_2	<dbl+lbl> 7, 6, 3, 5, 4, 3, 3, 5, 2, 3, 4, 3, 6, 4~
\$ effec_pm_1	<dbl+lbl> 1, 1, 6, 1, 4, 4, 3, 3, 2, 5, 7, 5, 5, 4~
\$ effec_pm_2	<dbl+lbl> 7, 6, 3, 4, 3, 4, 3, 4, 2, 4, 7, 5, 3, 4~
\$ poli_progre_1	<dbl+lbl> 7, 7, 5, 6, 7, 2, 7, 6, 6, 6, 7, 6, 5, 6~
\$ poli_progre_2	<dbl+lbl> 7, 7, 5, 6, 7, 3, 5, 7, 6, 6, 7, 6, 6, 6~
\$ poli_restri_1	<dbl+lbl> 7, 4, 6, 1, 6, 3, 4, 4, 4, 6, 6, 3, 4, 5~
\$ poli_restri_2	<dbl+lbl> 3, 6, 5, 1, 4, 3, 2, 6, 3, 4, 7, 5, 5, 5~
\$ aut_pw_1	<dbl+lbl> 7, 6, 3, 5, 5, 4, 2, 2, 3, 4, 7, 3, 3, 4~
\$ aut_pm_1	<dbl+lbl> 7, 6, 3, 5, 4, 4, 2, 3, 4, 4, 7, 2, 3, 4~
\$ depe_pw_1	<dbl+lbl> 6, 2, 5, 1, 6, 4, 5, 4, 4, 4, 7, 5, 5, 5~
\$ depe_pm_1	<dbl+lbl> 6, 3, 5, 1, 6, 4, 5, 4, 4, 4, 7, 5, 5, 5~
\$ condi_viole	<dbl+lbl> 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1~
\$ hara_pw_1	<dbl+lbl> 7, 6, 3, 7, 5, 5, 5, 5, 5, 6, 4, 5, 4, 4~
\$ hara_pw_2	<dbl+lbl> 7, 7, 7, 7, 7, 7, 7, 6, 7, 7, 7, 7, 5, 4~
\$ hara_pw_3	<dbl+lbl> 7, 6, 2, 7, 6, 7, 7, 5, 6, 7, 7, 7, 6, 4~
\$ abu_pw_1	<dbl+lbl> 7, 7, 3, 7, 5, 7, 7, 6, 6, 7, 7, 7, 7, 5~
\$ abu_pw_2	<dbl+lbl> 7, 7, 4, 7, 6, 7, 7, 7, 7, 7, 7, 7, 7, 5~
\$ abu_pw_3	<dbl+lbl> 7, 7, 6, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 6~
\$ viole_pw_1	<dbl+lbl> 7, 5, 7, 2, 3, 3, 3, 6, 4, 7, 6, 5, 2, 3~
\$ viole_pw_2	<dbl+lbl> 7, 6, 7, 2, 5, 4, 4, 5, 4, 6, 6, 5, 3, 3~
\$ viole_pw_3	<dbl+lbl> 7, 7, 6, 2, 7, 4, 4, 6, 6, 7, 6, 5, 5, 3~
\$ viole_pw_4	<dbl+lbl> 7, 5, 6, 2, 5, 4, 4, 6, 4, 6, 6, 4, 2, 3~
\$ viole_pw_5	<dbl+lbl> 7, 2, 6, 2, 2, 3, 4, 4, 7, 6, 4, 3, 3, 3~
\$ viole_pw_6	<dbl+lbl> 7, 6, 5, 2, 6, 5, 4, 6, 6, 6, 7, 4, 4, 3~
\$ barri_pw_1	<dbl+lbl> 6, 5, 7, 2, 2, 3, 6, 6, 6, 7, 7, 7, 5, 2~
\$ barri_pw_2	<dbl+lbl> 6, 1, 7, 2, 1, 3, 5, 7, 6, 7, 7, 6, 3, 2~
\$ barri_pw_3	<dbl+lbl> 6, 6, 6, 2, 4, 4, 3, 7, 6, 6, 7, 4, 5, 2~
\$ barri_pw_4	<dbl+lbl> 6, 3, 6, 2, 3, 4, 6, 7, 6, 6, 7, 4, 2, 2~
\$ barri_pw_5	<dbl+lbl> 6, 6, 5, 2, 6, 4, 6, 5, 4, 7, 7, 3, 3, 2~
\$ perpe_1	<dbl+lbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
\$ perpe_2	<dbl+lbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~

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$ perpe_3      <dbl+lbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ perpe_4      <dbl+lbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ perpe_5      <dbl+lbl> 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ age          <dbl+lbl> 54, 58, 57, 30, 25, 22, 27, 29, 22, 41, ~
$ sex          <dbl+lbl> 2, 1, 2, 1, 2, 2, 1, 1, 1, 2, 1, 1, 2, 2~
$ sex_other    <chr> "", "", "", "", "", "", "", "", "", "", "", ~
$ edu          <dbl+lbl> 5, 5, 5, 6, 5, 5, 5, 4, 5, 5, 6, 5, 6, 6~
$ ses          <dbl+lbl> 6, 6, 6, 7, 7, 7, 6, 5, 5, 4, 6, 8, 6, 5~
$ hig_ide      <dbl+lbl> 2, 1, 1, 4, 2, 4, 1, 2, 2, 1, 3, 4, 3, 3~
$ mid_ide      <dbl+lbl> 5, 6, 6, 6, 6, 5, 4, 6, 4, 3, 7, 6, 6, 5~
$ low_ide      <dbl+lbl> 3, 1, 2, 2, 1, 2, 3, 2, 3, 5, 1, 3, 2, 2~
$ po           <dbl+lbl> 1, 2, 2, 3, 2, 5, 1, 2, 2, 1, 5, 6, 6, 3~
$ country_residence <dbl+lbl> 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9~
$ country_residence_other <chr> "", "", "", "", "", "", "", "", "", "", "", ~
$ country_residence_recoded <dbl+lbl> 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9~
$ lang         <dbl+lbl> 1, 1, 3, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ lang_other    <chr> "", "", "Catalán", "Catalán", "", "", "", ""~
$ lang_recoded  <dbl+lbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ inc          <dbl> 3200, 1300, 3000, 60000, 3500, 600, 1800, 70~
$ currency      <dbl+lbl> 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7~
$ post_code     <chr> "40197", "47001", "08020", "00001", "41005",~
$ municipality  <chr> "Segovia", "Valladolid", "sant marti", "-", ~
$ n_perso       <dbl+lbl> 3, 1, 4, 2, 3, 3, 3, 2, 1, 3, 1, 3, 4, 1~
$ ori_sex       <dbl+lbl> 1, 1, 1, 1, 1, 1, 1, 1, 3, 1, 1, 1, 1, 1~
$ ori_sex_other <chr> "", "", "", "", "", "", "", "", "", "", "", ~
$ relation      <dbl+lbl> 1, 2, 1, 1, 1, 2, 1, 1, 2, 1, 2, 1, 1, 1~
$ natio_recoded <dbl+lbl> 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9~
$ regional_area <dbl+lbl> 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4~

```

We have 4,209 cases or rows and 212 variables or columns.

## 4 Functions

```

describe_kable <- function(data, vars) {
  psych::describe(data[, vars]) %>%
    kableExtra::kable(format = "markdown", digits = 3)
}

```

```

fit_correlations <- function(data, vars) {
  M <- cor(data[, vars], method = "pearson", use = "complete.obs")
  P <- psych::polychoric(data[, vars])

  diag(M) <- NA
  diag(P$rho) <- NA

  rnames <- paste0(LETTERS[1:length(vars)], ". ", vars)
  cnames <- paste0("(", LETTERS[1:length(vars)], ")")

  rownames(M) <- rnames
  colnames(M) <- cnames
  rownames(P$rho) <- rnames
  colnames(P$rho) <- cnames

  list(pearson = M, polychoric = P$rho)
}

corr_plots <- function(cor_list, data, db_name = "SOGEDI") {
  p1 <- wrap_elements(
    ~corrplot::corrplot(
      cor_list$pearson,
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      rect.col = "black",
      addCoef.col = "white",
      cl.cex = 0.8,
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = 'I. Pearson correlations')

  p2 <- wrap_elements(
    ~corrplot::corrplot(

```



```

      cor_list$polychoric,
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      rect.col = "black",
      addCoef.col = "white",
      cl.cex = 0.8,
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = 'II. Polychoric correlations')

p1 / p2 +
  plot_annotation(
    caption = paste0(
      "Source: Authors calculation based on ", db_name,
      " database (n=", nrow(data), ")"
    )
  )
}

alphas <- function(data, vars, new_var) {
  alpha_cronbach <- psych::alpha(data[, vars])
  raw_alpha <- alpha_cronbach$total$raw_alpha

  poly_matrix <- psych::polychoric(data[, vars])
  alpha_ordinal <- psych::alpha(poly_matrix$rho)
  ord_alpha <- alpha_ordinal$total$raw_alpha

  data[[new_var]] <- rowMeans(data[, vars], na.rm = TRUE)
  new_var_summary <- summary(data[[new_var]])

  list(
    raw_alpha      = raw_alpha,
    ord_alpha      = ord_alpha,

```

```

    new_var_summary = new_var_summary
  )
}

cfa_tables <- function(model) {

  sum_loadings <- standardizedSolution(model) %>%
    filter(op == "=~") %>%
    select(lhs, rhs, est.std) %>%
    rename(
      Factor    = lhs,
      Indicator = rhs,
      Loading   = est.std
    )

  loadings_table <- sum_loadings %>%
    kableExtra::kable(
      format      = "markdown",
      digits      = 3,
      booktabs    = TRUE,
      col.names   = c("Factor", "Indicator", "Loading"),
      caption     = NULL
    ) %>%
    kableExtra::kable_styling(
      full_width  = FALSE,
      font_size   = 10,
      latex_options = "HOLD_position",
      bootstrap_options = c("striped", "bordered")
    )

  sum_fit <- fitmeasures(model, output = "matrix")[c("chisq", "df", "cfi", "tli", "rmsea",
  sum_fit$nobs <- nobs(model)
  sum_fit$est <- "DWLS"
  sum_fit <- data.frame(sum_fit) %>%
    mutate(rmse.ci = paste0(rmse, "(", rmse.ci.lower, "-", rmse.ci.upper, ")")) %>%
    select(nobs, est, chisq, df, cfi, tli, rmse.ci)

  colnames_fit <- c("$N$", "Estimator", "$\\chi^2$", "df", "CFI", "TLI", "RMSEA (95%)")

  fit_table <- sum_fit %>%

```

```

kableExtra::kable(
  format      = "markdown",
  digits      = 3,
  booktabs    = TRUE,
  col.names   = colnames_fit,
  caption     = NULL
) %>%
kableExtra::kable_styling(
  full_width  = TRUE,
  font_size   = 10,
  latex_options = "HOLD_position",
  bootstrap_options = c("striped", "bordered")
)

list(
  loadings_table = loadings_table,
  fit_table      = fit_table
)
}

```

## 5 Processing

### 5.1 Block 1. Class inequality / Attitudes

#### 5.1.1 Perception of economic inequality in daily live

```
describe_kable(db_proc, c("eco_in_1", "eco_in_2", "eco_in_3"))
```

Table 1: Descriptive statistics of Perception of economic inequality in daily live

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
eco_in_1	1	4209	5.789	1.410	6	6.007	1.483	1	7	6	-	0.961	0.022
											1.167		
eco_in_2	2	4209	5.794	1.468	6	6.040	1.483	1	7	6	-	0.859	0.023
											1.204		

Table 1: Descriptive statistics of Perception of economic inequality in daily live

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
eco_in_3	3	4209	5.734	1.557	6	6.009	1.483	1	7	6	-1.251	0.954	0.024

```
# 1. Correlations
```

```
# fit pearson and polychoric
```

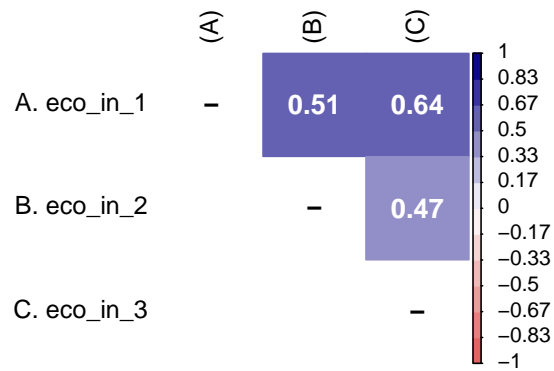
```
res1 <- fit_correlations(db_proc, c("eco_in_1", "eco_in_2", "eco_in_3"))
```

```
#Plot the matrix using corrplot
```

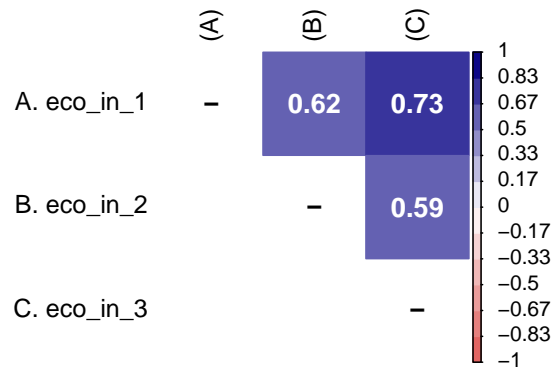
```
corr_plots(res1, db_proc, "SOGEDI")
```

Figure 1: Correlation matrixes of Perception of economic inequality in daily live

I. Pearson correlations



II. Polychoric correlations



Source: Authors calculation based on SOGEDl database (n=4209)

```
# 2. Alpha
```

```
mi_variable <- "eco_in"
result1 <- alphas(db_proc, c("eco_in_1", "eco_in_2", "eco_in_3"), mi_variable)

result1$raw_alpha
```

```
[1] 0.7778003
```

```
result1$ord_alpha
```

```
[1] 0.8475093
```

```
result1$new_var_summary
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.000	5.000	6.000	5.773	7.000	7.000

```
# 3. CFA
```

```
# model
```

```
model_cfa <- ' perc_eco_inequality =~ eco_in_1 + eco_in_2 + eco_in_3 '
```

```
# estimation
```

```
m1_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "DWLS",
              ordered = T,
              std.lv = F)
```

```
cfa_tables(m1_cfa)$loadings_table
```

Table 2: Standardized Factor Loadings of Perception of economic inequality in daily live

Factor	Indicator	Loading
perc_eco_inequality	eco_in_1	0.876
perc_eco_inequality	eco_in_2	0.710
perc_eco_inequality	eco_in_3	0.836

```
cfa_tables(m1_cfa)$fit_table
```

Table 3: Summary fit indices of Perception of economic inequality in daily live

$N$	Estimator	$\chi^2$	df	CFI	TLI	RMSEA (95%)
4209	DWLS	0	0	1	1	0(0-0)

### 5.1.2 Protective paternalism toward poor women and men

```
describe_kable(db_proc, c("pp_pw_1", "pp_pw_2", "pp_pw_3", "pp_pw_4", "pp_pm_1", "pp_p
```

Table 4: Descriptive statistics of Protective paternalism toward poor women and men

vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
pp_pw_1	4209	5.401	1.665	6	5.641	1.483	1	7	6	-0.929	0.150	0.026
pp_pw_2	4209	5.188	1.707	5	5.401	1.483	1	7	6	-0.741	-0.222	0.026
pp_pw_3	4209	5.249	1.686	5	5.466	1.483	1	7	6	-0.795	-0.083	0.026
pp_pw_4	4209	5.233	1.658	5	5.431	1.483	1	7	6	-0.736	-0.149	0.026
pp_pm_1	4209	5.338	1.661	6	5.560	1.483	1	7	6	-0.839	-0.034	0.026
pp_pm_2	4209	5.098	1.708	5	5.292	1.483	1	7	6	-0.664	-0.326	0.026
pp_pm_3	4209	5.185	1.711	5	5.395	1.483	1	7	6	-0.722	-0.286	0.026
pp_pm_4	4209	5.156	1.699	5	5.356	1.483	1	7	6	-0.695	-0.296	0.026

```
# 1. Correlations ppw

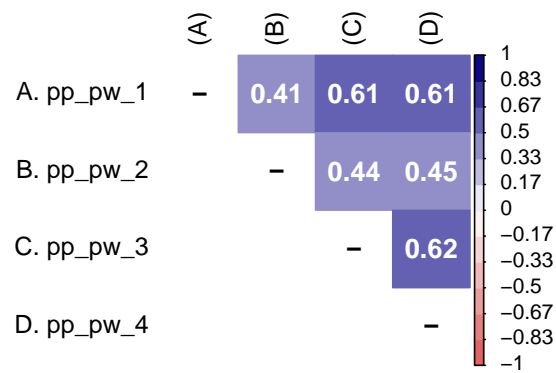
# fit pearson and polychoric
res2 <- fit_correlations(db_proc, c("pp_pw_1", "pp_pw_2", "pp_pw_3", "pp_pw_4"))

res3 <- fit_correlations(db_proc, c("pp_pm_1", "pp_pm_2", "pp_pm_3", "pp_pm_4"))

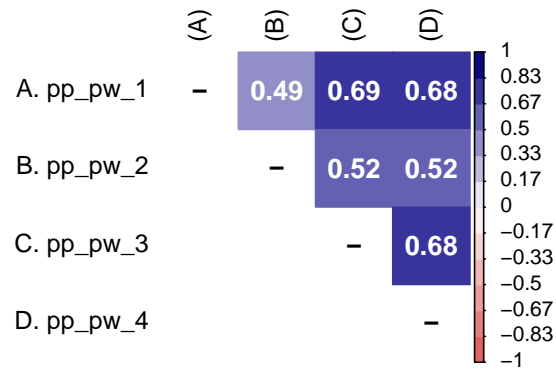
#Plot the matrix using corrplot
corr_plots(res2, db_proc, "SOGEDI")
```

Figure 2: Correlation matrixes of Protective paternalism toward poor women

I. Pearson correlations



II. Polychoric correlations



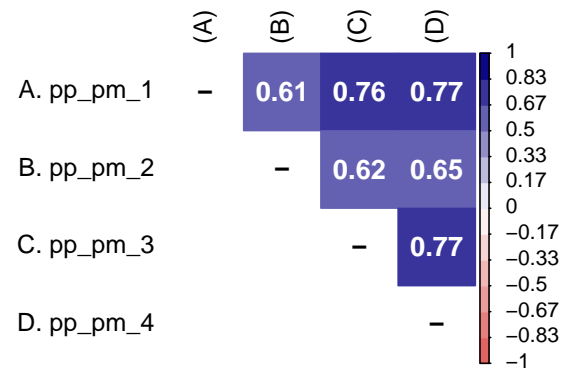
Source: Authors calculation based on SOGEDl database (n=4209)

```
#Plot the matrix using corrplot
corr_plots(res3, db_proc, "SOGEDl")
```

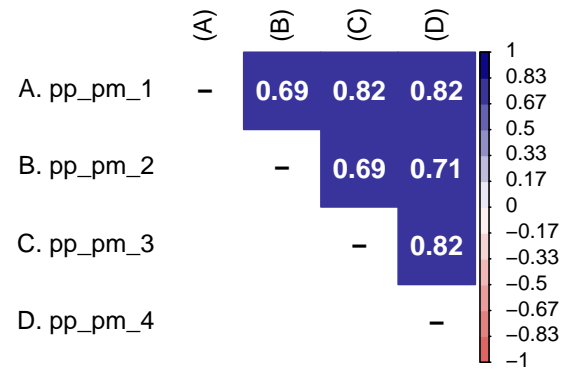


Figure 3: Correlation matrixes of Protective paternalism toward poor men

I. Pearson correlations



II. Polychoric correlations



Source: Authors calculation based on SOGEDl database (n=4209)

```
# 2. Alpha
```

```
mi_variable <- "pp_pw"
```

```
result2 <- alphas(db_proc, c("pp_pw_1", "pp_pw_2", "pp_pw_3", "pp_pw_4"), mi_variable)
```

```
result2$raw_alpha
```

```
[1] 0.8144432
```

```
result2$ord_alpha
```

```
[1] 0.8555965
```

```
result2$new_var_summary
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.000	4.500	5.500	5.268	6.250	7.000

```
# 2. Alpha
```

```
mi_variable <- "pp_pm"
```

```
result3 <- alphas(db_proc, c("pp_pm_1", "pp_pm_2", "pp_pm_3", "pp_pm_4"), mi_variable)
```

```
result3$raw_alpha
```

```
[1] 0.901213
```

```
result3$ord_alpha
```

```
[1] 0.926433
```

```
result3$new_var_summary
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.000	4.250	5.250	5.194	6.500	7.000

Preguntar Mario por el CFA de esto: es por cada subdimension o toda la dimension?

### 5.1.3 Complementary class differentiation toward poor women and men

```
describe_kable(db_proc, c("cc_pw_1", "cc_pw_2", "cc_pw_3", "cc_pw_4", "cc_pm_1", "cc_p
```

Table 5: Descriptive statistics of Complementary class diferenciation toward poor women and men

vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
cc_pw_11	4209	5.353	1.585	6	5.536	1.483	1	7	6	-	-	0.024
										0.711	0.236	
cc_pw_22	4209	3.702	1.680	4	3.658	1.483	1	7	6	0.055	-	0.026
											0.498	
cc_pw_33	4209	3.858	1.808	4	3.822	1.483	1	7	6	0.020	-	0.028
											0.792	
cc_pw_44	4209	4.340	1.869	4	4.425	1.483	1	7	6	-	-	0.029
										0.307	0.828	
cc_pm_15	4209	4.874	1.676	5	4.993	1.483	1	7	6	-	-	0.026
										0.333	0.702	
cc_pm_26	4209	3.524	1.609	4	3.462	1.483	1	7	6	0.125	-	0.025
											0.411	
cc_pm_37	4209	3.593	1.680	4	3.530	1.483	1	7	6	0.150	-	0.026
											0.560	
cc_pm_48	4209	4.137	1.820	4	4.172	1.483	1	7	6	-	-	0.028
										0.136	0.827	

```
# 1. Correlations ppw

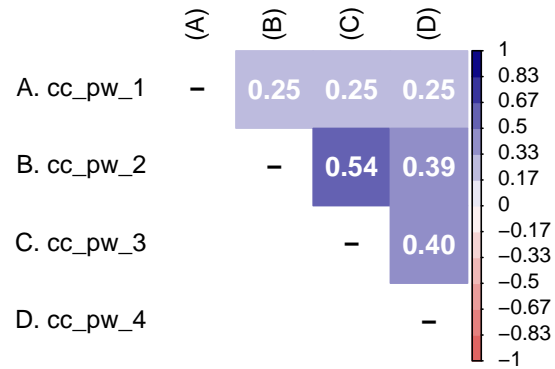
# fit pearson and polychoric
res2 <- fit_correlations(db_proc, c("cc_pw_1", "cc_pw_2", "cc_pw_3", "cc_pw_4"))

res3 <- fit_correlations(db_proc, c("cc_pm_1", "cc_pm_2", "cc_pm_3", "cc_pm_4"))

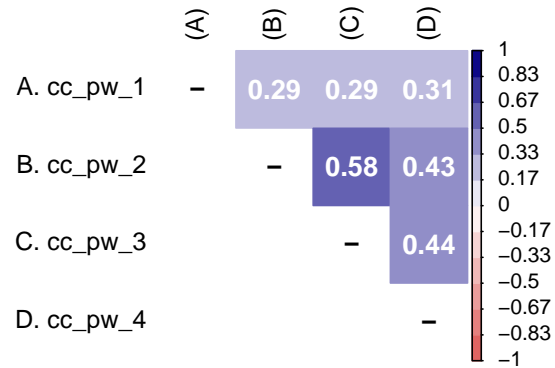
#Plot the matrix using corrplot
corr_plots(res2, db_proc, "SOGEDI")
```

Figure 4: Correlation matrixes of Complementary class diferenciation toward poor women

I. Pearson correlations



II. Polychoric correlations

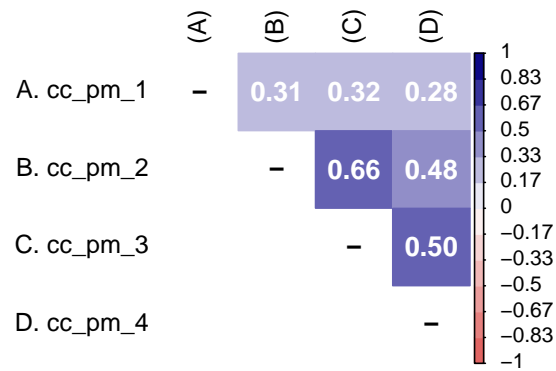


Source: Authors calculation based on SOGEDl database (n=4209)

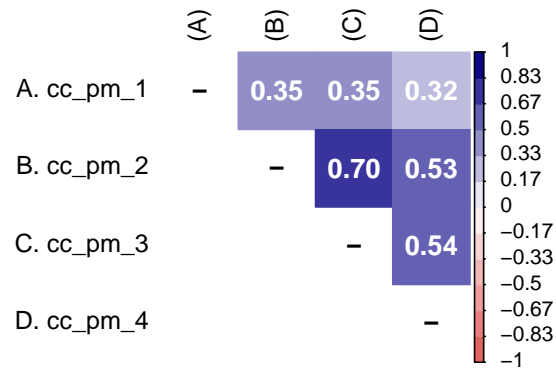
```
#Plot the matrix using corrplot
corr_plots(res3, db_proc, "SOGEDl")
```

Figure 5: Correlation matrixes of Complementary class diferenciation toward poor men

I. Pearson correlations



II. Polychoric correlations



Source: Authors calculation based on SOGEDl database (n=4209)

```
# 2. Alpha
```

```
mi_variable <- "cc_pw"
result2 <- alphas(db_proc, c("cc_pw_1", "cc_pw_2", "cc_pw_3", "cc_pw_4"), mi_variable)

result2$raw_alpha
```

```
[1] 0.6841424
```

```
result2$ord_alpha
```

```
[1] 0.7191139
```

```
result2$new_var_summary
```

```
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.000   3.500   4.250   4.313   5.000   7.000
```

```
# 2. Alpha
```

```
mi_variable <- "cc_pm"
```

```
result3 <- alphas(db_proc, c("cc_pm_1", "cc_pm_2", "cc_pm_3", "cc_pm_4"), mi_variable)
```

```
result3$raw_alpha
```

```
[1] 0.7443716
```

```
result3$ord_alpha
```

```
[1] 0.7760468
```

```
result3$new_var_summary
```

```
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.000   3.250   4.000   4.032   4.750   7.000
```

### 5.1.4 Hostile classism toward poor women and men

```
describe_kable(db_proc, c("hc_pw_1", "hc_pw_2", "hc_pw_3", "hc_pw_4", "hc_pm_1", "hc_pm_2"))
```

Table 6: Descriptive statistics of Hostile classism toward poor women and men

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
hc_pw_11		4209	2.474	1.600	2	2.256	1.483	1	7	6	0.871	-0.105	0.025
hc_pw_22		4209	2.929	1.862	3	2.714	2.965	1	7	6	0.610	-0.734	0.029

Table 6: Descriptive statistics of Hostile classism toward poor women and men

vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
hc_pw_33	4209	2.616	1.697	2	2.400	1.483	1	7	6	0.771	-0.367	0.026
hc_pw_44	4209	3.189	1.817	3	3.039	2.965	1	7	6	0.372	-0.845	0.028
hc_pm_15	4209	3.064	1.731	3	2.917	1.483	1	7	6	0.408	-0.717	0.027
hc_pm_26	4209	3.229	1.804	3	3.084	1.483	1	7	6	0.373	-0.805	0.028
hc_pm_37	4209	3.118	1.730	3	2.978	1.483	1	7	6	0.373	-0.728	0.027
hc_pm_48	4209	3.618	1.831	4	3.547	1.483	1	7	6	0.116	-0.919	0.028

```
# 1. Correlations ppw

# fit pearson and polychoric
res2 <- fit_correlations(db_proc, c("hc_pw_1","hc_pw_2","hc_pw_3","hc_pw_4"))

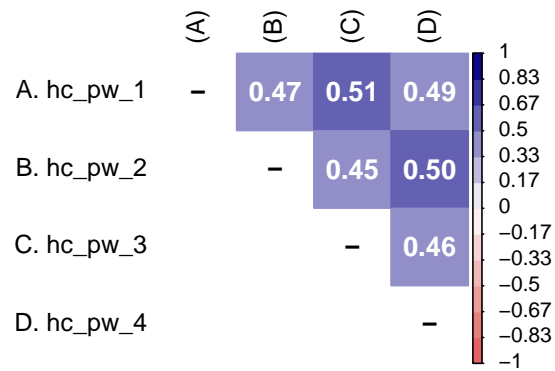
res3 <- fit_correlations(db_proc, c("hc_pm_1","hc_pm_2","hc_pm_3","hc_pm_4"))

#Plot the matrix using corrplot

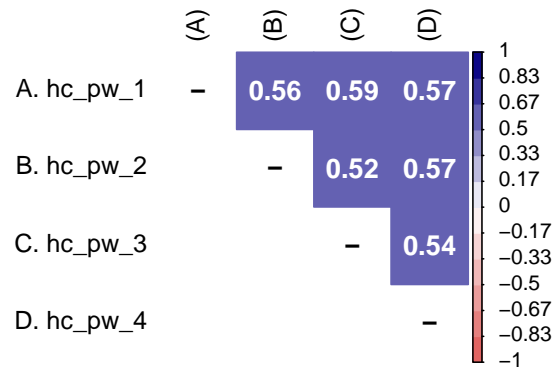
corr_plots(res2, db_proc, "SOGEDI")
```

Figure 6: Correlation matrixes of Hostile classism toward poor women

I. Pearson correlations



II. Polychoric correlations



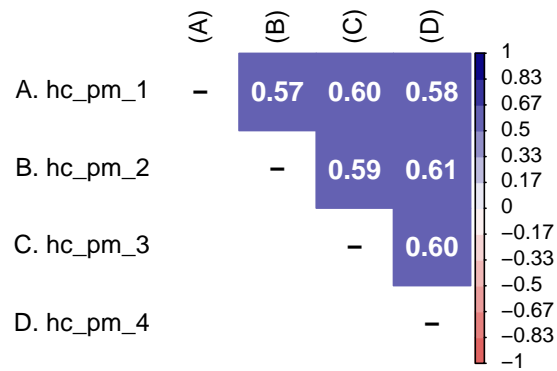
Source: Authors calculation based on SOGEDl database (n=4209)

```
#Plot the matrix using corrplot
corr_plots(res3, db_proc, "SOGEDl")
```

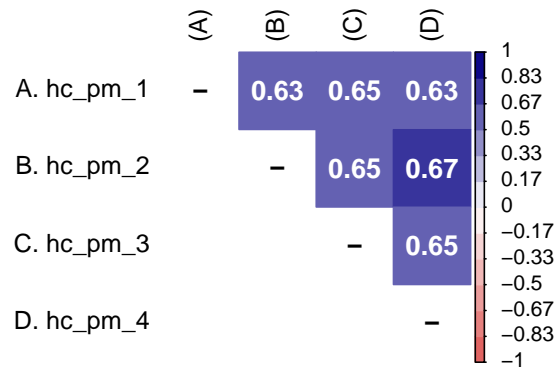


Figure 7: Correlation matrixes of Hostile classism toward poor men

I. Pearson correlations



II. Polychoric correlations



Source: Authors calculation based on SOGEDl database (n=4209)

```
# 2. Alpha
```

```
mi_variable <- "hc_pw"
result2 <- alphas(db_proc, c("hc_pw_1","hc_pw_2","hc_pw_3","hc_pw_4"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7858148
```

```
result2$ord_alpha
```

```
[1] 0.8336523
```

```
result2$new_var_summary
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.000	1.750	2.750	2.802	3.750	7.000

```
# 2. Alpha
```

```
mi_variable <- "hc_pm"
```

```
result3 <- alphas(db_proc, c("hc_pm_1","hc_pm_2","hc_pm_3","hc_pm_4"), mi_variable)
```

```
result3$raw_alpha
```

```
[1] 0.8526135
```

```
result3$ord_alpha
```

```
[1] 0.8796202
```

```
result3$new_var_summary
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.000	2.000	3.250	3.257	4.250	7.000