Calculation and analysis of variables

Socioeconomic and Gender Disparities: A Multi-Country Study

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1 Presentation

This document presents the code employed for calculating and analyzing the variables in the project Socioeconomic and Gender Disparities: A Multi-Country Study. The dataset used, `db_proc.RData`, is derived from a previously processed source.

A descriptive analysis is conducted for all survey items, covering both single variables and those that form part of composite indicators or latent factors. For the latter, correlation matrices and Reliability indices (Cronbach's alpha) are also computed. In several instances, we evaluate factorial structures on the basis of the original sources and the publications from which the items were adapted, while remaining open to alternative configurations during the data exploration phase.

Data processing and variable construction are organized according to the SOGEDI survey modules. For those items whose Reliability or factorial structure prove insufficient, we make recommendations for their use in empirical research.

In order to assess the multivariate normality of the items included in the measurement models, we apply Mardia's test, which evaluates deviations in both skewness and kurtosis (Mardia, 1970). A statistically significant result suggests that the data deviate from a multivariate normal distribution, underscoring the need to use estimation methods suited to potential non-normality.

The following fit criteria, drawn from Brown (2015) and Kline (2023), guide the evaluation of model adequacy:

- Chi-square: p>0.05
- Chi-square ratio (χ^2/df): < 3

- Comparative Fit Index (CFI): > 0.95
- Tucker–Lewis Index (TLI): > 0.95
- Root Mean Square Error of Approximation (RMSEA): < 0.06
- Standardized Root Mean Square Residual (SRMR): < 0.08
- Akaike Information Criterion (AIC): no fixed cutoff; lower values indicate better fit.

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,
               sjmisc,
               sjPlot,
               here,
               lavaan,
               psych,
               rstatix,
               ggdist,
               patchwork,
               sjlabelled,
               gtools,
               haven)

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              <dttm> 2024-04-28 11:11:20, 2024-04-28 11:12:34, 2~
$ EndDate                <dttm> 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           <dttm> 2024-04-28 11:30:12, 2024-04-28 11:31:16, 2~
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$ LocationLongitude      <chr> "-4.7435", "2.1606", "2.2164", "2.4414", "-5~
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$ eco_in_3               <dbl+lbl> 7, 6, 7, 6, 6, 4, 2, 3, 5, 3, 5, 4, 6, 6~
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$ pp_pw_3                <dbl+lbl> 7, 6, 7, 2, 5, 3, 3, 5, 2, 4, 2, 4, 5, 5~
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$ gen_in_6                 <dbl+lbl> 6, 7, 5, 6, 4, 2, 5, 7, 6, 6, 7, 5, 7, 4~
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$ ge_ra_me                 <dbl> 30, 30, 40, 40, 60, 80, 50, 80, 73, 40, 15, ~
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$ condi_class              <dbl+lbl> 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1~
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$ ah_2                     <dbl+lbl> 2, 1, 2, 1, 5, 2, 2, 1, 1, 1, 1, 1, 1, 2~
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$ af_2                     <dbl+lbl> 1, 3, 2, 7, 4, 4, 2, 7, 4, 5, 4, 4, 5, 4~
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$ co_2                     <dbl+lbl> 2, 2, 2, 1, 6, 2, 2, 1, 4, 1, 1, 3, 4, 2~
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$ in_po_1                  <dbl+lbl> NA, NA,  4,  2, NA, NA, NA,  4, NA,  4, ~
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$ 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, ~
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$ wel_abu_2               <dbl+lbl> 1, 1, 2, 1, 2, 2, 3, 2, 1, 2, 2, 4, 3, 5~
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$ wel_pa_2                <dbl+lbl> 7, 2, 7, 1, 6, 2, 5, 6, 4, 6, 7, 7, 5, 5~
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$ wel_ho_2                <dbl+lbl> 1, 1, 1, 1, 2, 2, 4, 4, 1, 6, 1, 4, 2, 5~
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$ ris_rw                  <dbl+lbl> 3, 1, 5, 1, 4, 4, 3, 3, 5, 5, 5, 4, 2, 4~
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$ 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~
$ perpe_3                   <dbl+lbl> 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~
$ perpe_5                   <dbl+lbl> 1, 1, 1, 1, 2, 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

In order to streamline the processing and calculation of variables, we develop a series of functions that automate specific statistical analyses and table generation.

```
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")

  diag(M) <- NA

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

  rownames(M) <- rnames
  colnames(M) <- cnames

  return(M)
}


alphas <- function(data, vars, new_var) {
```

```
  alpha_cronbach <- psych::alpha(data[, vars])
  raw_alpha <- alpha_cronbach$total$raw_alpha

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

  list(
    raw_alpha       = raw_alpha,
    new_var_summary = new_var_summary
  )
}


cfa_tab_fit <- function(models,
                              country_names = NULL,
                              colnames_fit  = c("","$N$","Estimator","$\\chi^2$ (df)",


  get_fit_df <- function(model) {
    sum_fit <- fitmeasures(model, output = "matrix")[c("chisq","pvalue","df","cfi","tl
                                                       "rmsea","rmsea.ci.lower","rmsea
                                                       "srmr", "aic"),]
    sum_fit$nobs <- nobs(model)
    sum_fit$est  <- summary(model)$optim$estimator
    sum_fit <- data.frame(sum_fit) %>%
      dplyr::mutate(
        dplyr::across(
          .cols = c(cfi, tli, rmsea, rmsea.ci.lower, rmsea.ci.upper, srmr, aic),
          .fns  = ~ round(., 3)
        ),
        stars   = gtools::stars.pval(pvalue),
        chisq   = paste0(round(chisq,3), " (", df, ") ", stars),
        rmsea.ci= paste0(rmsea, " [", rmsea.ci.lower, "-", rmsea.ci.upper, "]")
      ) %>%
      dplyr::select(nobs, est, chisq, cfi, tli, rmsea.ci, srmr, aic)

    return(sum_fit)
  }

  fit_list <- purrr::map(models, get_fit_df)
```

```
  for (i in seq_along(fit_list)) {
    fit_list[[i]]$country <- country_names[i]
  }

  sum_fit <- dplyr::bind_rows(fit_list)

  fit_table <- sum_fit %>%
    dplyr::select(country, dplyr::everything()) %>%
    kableExtra::kable(
      format     = "markdown",
      digits     = 3,
      booktabs   = TRUE,
      col.names  = colnames_fit,
      caption    = NULL
    ) %>%
    kableExtra::kable_styling(
      full_width        = TRUE,
      font_size         = 11,
      latex_options     = "HOLD_position",
      bootstrap_options = c("striped", "bordered")
    )

  return(
    list(
      fit_table = fit_table,
      sum_fit = sum_fit)
  )
}


fit_correlations_pairwise <- function(data, vars) {
  M <- cor(data[, vars], method = "pearson", use = "pairwise.complete.obs")

  diag(M) <- NA

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

  rownames(M) <- rnames
  colnames(M) <- cnames
```

```
  return(M)
}
```

5 Processing and analysis

5.1 Block 1. Class inequality / Attitudes

5.1.1 Perception of economic inequality in daily live

The items to capture individual subjective perception of daily economic inequality came from previous research from García-Castro et al. (2019). For the SOGEDI study we selected the items from the original scale that had the highest saturation on the construct and could potentially be more suitable for application in different countries.

Descriptive analysis

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

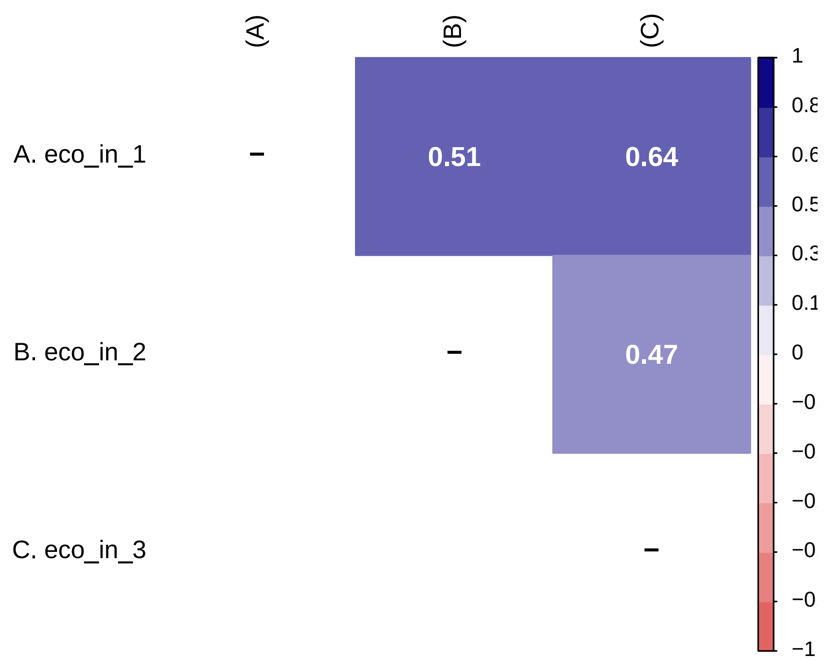
Table 1: Descriptive statistics of Perception of economic inequality in daily live

	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	-1.167	0.961	0.022
eco_in_2	2	4209	5.794	1.468	6	6.040	1.483	1	7	6	-1.204	0.859	0.023
eco_in_3	3	4209	5.734	1.557	6	6.009	1.483	1	7	6	-1.251	0.954	0.024

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("eco_in_1", "eco_in_2", "eco_in_3")),
      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(caption = paste0(
  "Source: Authors calculation based on SOGEDI",
  " database (n=", nrow(db_proc), ")"
))
```

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



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

Reliability

```
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$new_var_summary
```

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

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("eco_in_1", "eco_in_2", "eco_in_3")], n
```

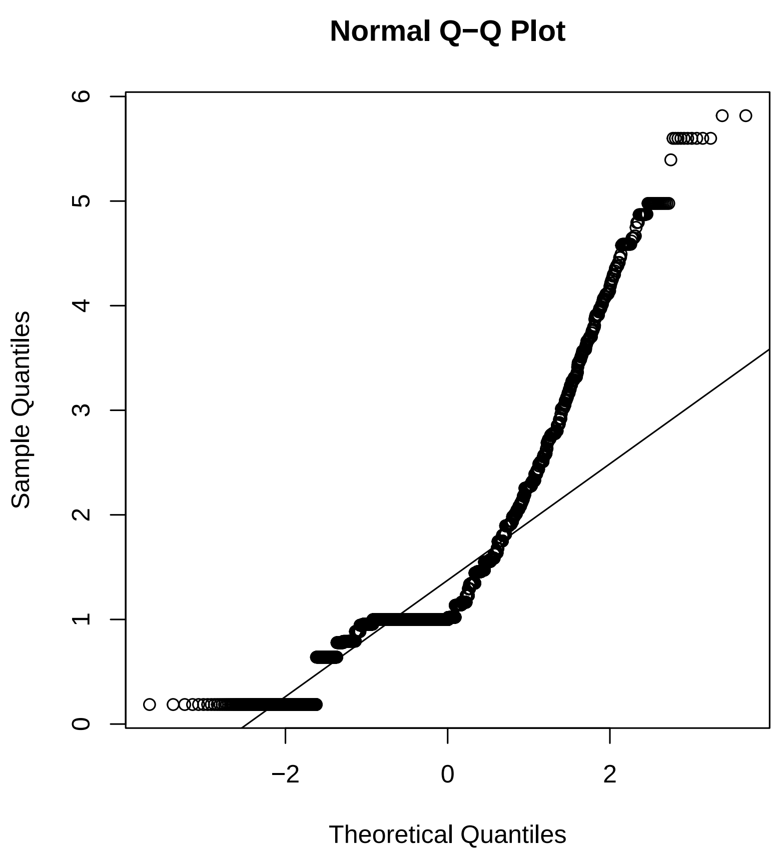
Confirmatory Factor Analysis

Mardia's test for evaluate multivariate normality.

```
mardia(db_proc[,c("eco_in_1", "eco_in_2", "eco_in_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("eco_in_1", "eco_in_2", "eco_in_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 3 b1p = 5.37 skew = 3767.2 with probability <= 0 small sample skew = 3771.23 with probability <= 0 b2p = 27.82 kurtosis = 75.95 with



probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```
# 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 = "MLR",
              ordered = F,
              std.lv = F)

m1_cfa_arg <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 1),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m1_cfa_cl <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 3),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m1_cfa_col <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 4),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m1_cfa_es <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 9),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m1_cfa_mex <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 13),
              estimator = "MLR",
```

```
              ordered = F,
              std.lv = F)
```

```
cfa_tab_fit(
  models = list(m1_cfa, m1_cfa_arg, m1_cfa_cl, m1_cfa_col, m1_cfa_es, m1_cfa_mex),
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$fit_table
```

Table 2: Summary fit indices of Perception of economic inequality in daily live

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	0 (0)	1	1	0 [0-0]	0	42001.068
Argentina	807	ML	0 (0)	1	1	0 [0-0]	0	8145.822
Chile	883	ML	0 (0)	1	1	0 [0-0]	0	8857.224
Colombia	833	ML	0 (0)	1	1	0 [0-0]	0	8228.138
Spain	835	ML	0 (0)	1	1	0 [0-0]	0	8033.080
México	846	ML	0 (0)	1	1	0 [0-0]	0	8556.013

5.1.2 Socioeconomic inequality justification

The item to capture individual justification of socioeconomic inequality was created by the project team.

Descriptive analysis

```
psych::describe(db_proc$jus_ine) %>%
    kableExtra::kable(format = "markdown", digits = 3)
```

Table 3: Descriptive statistics of Socioeconomic inequality justification

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	4209	2.295	1.755	1	2.295	0	1	7	6	1.3	0.669	0.027

5.1.3 Economic inequality collective action

The item to capture individual collective action toward economic inequality was adapted from Fresno-Díaz et al. (2023).

Descriptive analysis

```
psych::describe(db_proc$co_eco) %>%
    kableExtra::kable(format = "markdown", digits = 3)
```

Table 4: Descriptive statistics of Economic inequality collective action

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	4209	4.55	1.988	5	4.55	2.965	1	7	6	-0.394	-0.951	0.031

5.1.4 Ambivalent classism

The items to capture ambivalent classism came from previous research from Sainz et al. (2021). For the SOGEDI study we used all items from the paternalistic/complementary dimensions of the scale adapted by the authors. For the hostile dimension, we selected the four items most strongly associated with the construct, based on the scale adaptation, while omitting items that could be misinterpreted in other spanish speaker contexts.

Protective paternalism toward poor women and men

Descriptive analysis

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

Table 5: 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	1	4209	5.401	1.665	6	5.641	1.483	1	7	6	-0.929	0.150	0.026

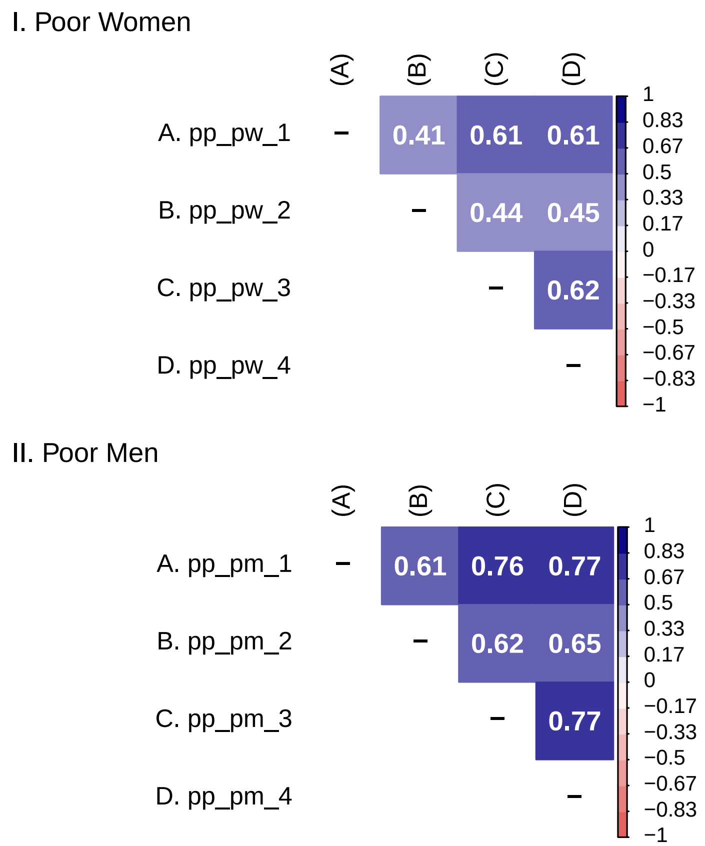
Table 5: Descriptive statistics of Protective paternalism toward poor women and men

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
pp_pw_2	2	4209	5.188	1.707	5	5.401	1.483	1	7	6	-0.741	-0.222	0.026
pp_pw_3	3	4209	5.249	1.686	5	5.466	1.483	1	7	6	-0.795	-0.083	0.026
pp_pw_4	4	4209	5.233	1.658	5	5.431	1.483	1	7	6	-0.736	-0.149	0.026
pp_pm_1	5	4209	5.338	1.661	6	5.560	1.483	1	7	6	-0.839	-0.034	0.026
pp_pm_2	6	4209	5.098	1.708	5	5.292	1.483	1	7	6	-0.664	-0.326	0.026
pp_pm_3	7	4209	5.185	1.711	5	5.395	1.483	1	7	6	-0.722	-0.286	0.026
pp_pm_4	8	4209	5.156	1.699	5	5.356	1.483	1	7	6	-0.695	-0.296	0.026

```r
p1 <- wrap_elements(
  ~corrplot::corrplot(
    fit_correlations(db_proc, c("pp_pw_1", "pp_pw_2", "pp_pw_3", "pp_pw_4")),
    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. Poor Women')

p2 <- wrap_elements(
  ~corrplot::corrplot(
    fit_correlations(db_proc, c("pp_pm_1", "pp_pm_2", "pp_pm_3", "pp_pm_4")),
```

```
    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. Poor Men')

p1 / p2 + labs(
          caption = paste0(
  "Source: Authors calculation based on SOGEDI",
  " database (n=", nrow(db_proc), ")"
))
```

Figure 2: Correlation matrices of Protective paternalism toward poor women and men



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

Reliability

```
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$new_var_summary
```

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

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("pp_pw_1", "pp_pw_2", "pp_pw_3", "pp_pw
```

```r
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
```

```r
result3$new_var_summary
```

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

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("pp_pm_1", "pp_pm_2", "pp_pm_3", "pp_pm
```

Complementary class diferenciation toward poor women and men

Descriptive analysis

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

Table 6: 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_1	1	4209	5.353	1.585	6	5.536	1.483	1	7	6	-0.711	-0.236	0.024
cc_pw_2	2	4209	3.702	1.680	4	3.658	1.483	1	7	6	0.055	-0.498	0.026
cc_pw_3	3	4209	3.858	1.808	4	3.822	1.483	1	7	6	0.020	-0.792	0.028
cc_pw_4	4	4209	4.340	1.869	4	4.425	1.483	1	7	6	-0.307	-0.828	0.029

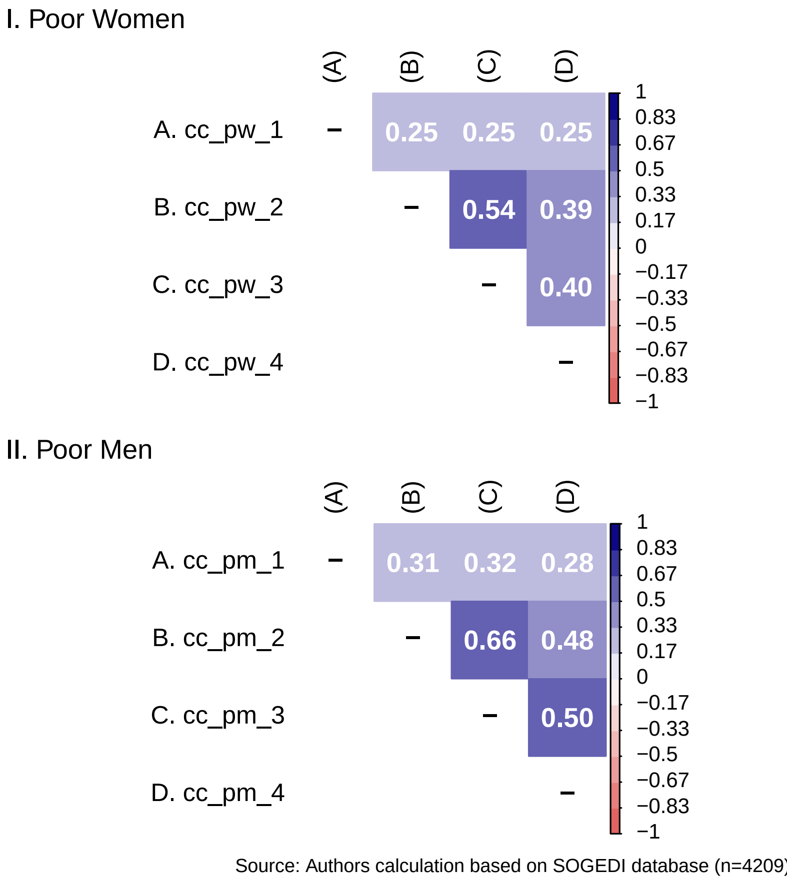
Table 6: Descriptive statistics of Complementary class diferenciation toward poor women and men

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
cc_pm_15		4209	4.874	1.676	5	4.993	1.483	1	7	6	-0.333	-0.702	0.026
cc_pm_26		4209	3.524	1.609	4	3.462	1.483	1	7	6	0.125	-0.411	0.025
cc_pm_37		4209	3.593	1.680	4	3.530	1.483	1	7	6	0.150	-0.560	0.026
cc_pm_48		4209	4.137	1.820	4	4.172	1.483	1	7	6	-0.136	-0.827	0.028

```r
p1 <- wrap_elements(
  ~corrplot::corrplot(
    fit_correlations(db_proc, c("cc_pw_1", "cc_pw_2", "cc_pw_3", "cc_pw_4")),
    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. Poor Women')

p2 <- wrap_elements(
  ~corrplot::corrplot(
    fit_correlations(db_proc, c("cc_pm_1", "cc_pm_2", "cc_pm_3", "cc_pm_4")),
    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. Poor Men')

p1 / p2 + labs(
         caption = paste0(
  "Source: Authors calculation based on SOGEDI",
  " database (n=", nrow(db_proc), ")"
))
```

Figure 3: Correlation matrices of Complementary class diferenciation toward poor women and men



Reliability

```
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$new_var_summary
```

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

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("cc_pw_1", "cc_pw_2", "cc_pw_3", "cc_pw
```

```
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$new_var_summary
```

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

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("cc_pm_1", "cc_pm_2", "cc_pm_3", "cc_pm
```

Hostile classism toward poor women and men

Descriptive analysis

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

Table 7: 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_1	1	4209	2.474	1.600	2	2.256	1.483	1	7	6	0.871	-0.105	0.025
hc_pw_2	2	4209	2.929	1.862	3	2.714	2.965	1	7	6	0.610	-0.734	0.029
hc_pw_3	3	4209	2.616	1.697	2	2.400	1.483	1	7	6	0.771	-0.367	0.026

Table 7: 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_4	4	4209	3.189	1.817	3	3.039	2.965	1	7	6	0.372	-0.845	0.028
hc_pm_1	5	4209	3.064	1.731	3	2.917	1.483	1	7	6	0.408	-0.717	0.027
hc_pm_2	6	4209	3.229	1.804	3	3.084	1.483	1	7	6	0.373	-0.805	0.028
hc_pm_3	7	4209	3.118	1.730	3	2.978	1.483	1	7	6	0.373	-0.728	0.027
hc_pm_4	8	4209	3.618	1.831	4	3.547	1.483	1	7	6	0.116	-0.919	0.028

```r
p1 <- wrap_elements(
  ~corrplot::corrplot(
    fit_correlations(db_proc, c("hc_pw_1", "h_pw_2", "hc_pw_3", "hc_pw_4")),
    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. Poor Women')

p2 <- wrap_elements(
  ~corrplot::corrplot(
    fit_correlations(db_proc, c("hc_pm_1", "hc_pm_2", "hc_pm_3", "hc_pm_4")),
    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. Poor Men')

p1 / p2 + labs(
         caption = paste0(
  "Source: Authors calculation based on SOGEDI",
  " database (n=", nrow(db_proc), ")"
))
```

Reliability

```
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$new_var_summary
```

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

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("hc_pw_1","hc_pw_2","hc_pw_3","hc_pw_4"
```

```
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$new_var_summary
```

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

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("hc_pm_1","hc_pm_2","hc_pm_3","hc_pm_4"
```

Confirmatory Factor Analysis

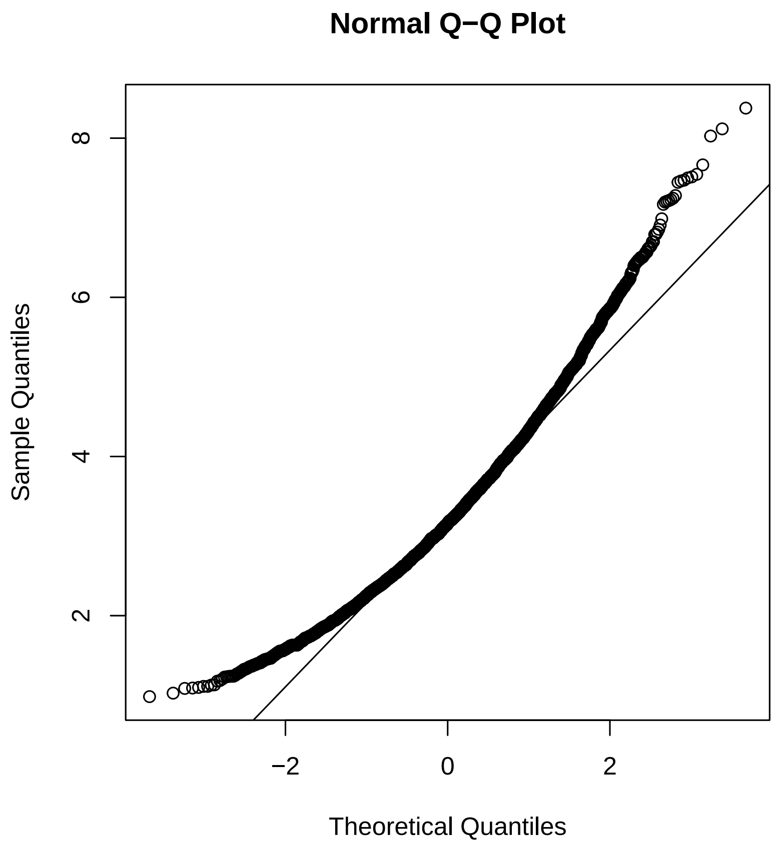
Ambilavent classim with woman as target

Mardia's test for evaluate multivariate normality.

```
mardia(db_proc[,c("pp_pw_1", "pp_pw_2", "pp_pw_3", "pp_pw_4",
                  "cc_pw_1", "cc_pw_2", "cc_pw_3", "cc_pw_4",
                  "hc_pw_1", "hc_pw_2", "hc_pw_3", "hc_pw_4")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("pp_pw_1", "pp_pw_2", "pp_pw_3", "pp_pw_4", "cc_pw_1", "cc_pw_2", "cc_pw_3", "cc_pw_4", "hc_pw_1", "hc_pw_2", "hc_pw_3", "hc_pw_4")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 12 b1p = 9.08 skew = 6371.73 with probability <= 0 small sample skew = 6376.97 with probability <= 0 b2p = 210.51 kurtosis = 75.24 with



probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```
# model
model_cfa <- '
  aci_pp =~ pp_pw_1 + pp_pw_2 + pp_pw_3 + pp_pw_4
  aci_cc =~ cc_pw_1 + cc_pw_2 + cc_pw_3 + cc_pw_4
  aci_hc =~ hc_pw_1 + hc_pw_2 + hc_pw_3 + hc_pw_4
  aci =~ aci_pp + aci_cc + aci_hc '

# estimation
m2_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "MLR",
              ordered = F,
```

```
              std.lv = F)

m2_cfa_arg <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 1),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m2_cfa_cl <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 3),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m2_cfa_col <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 4),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m2_cfa_es <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 9),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m2_cfa_mex <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 13),
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

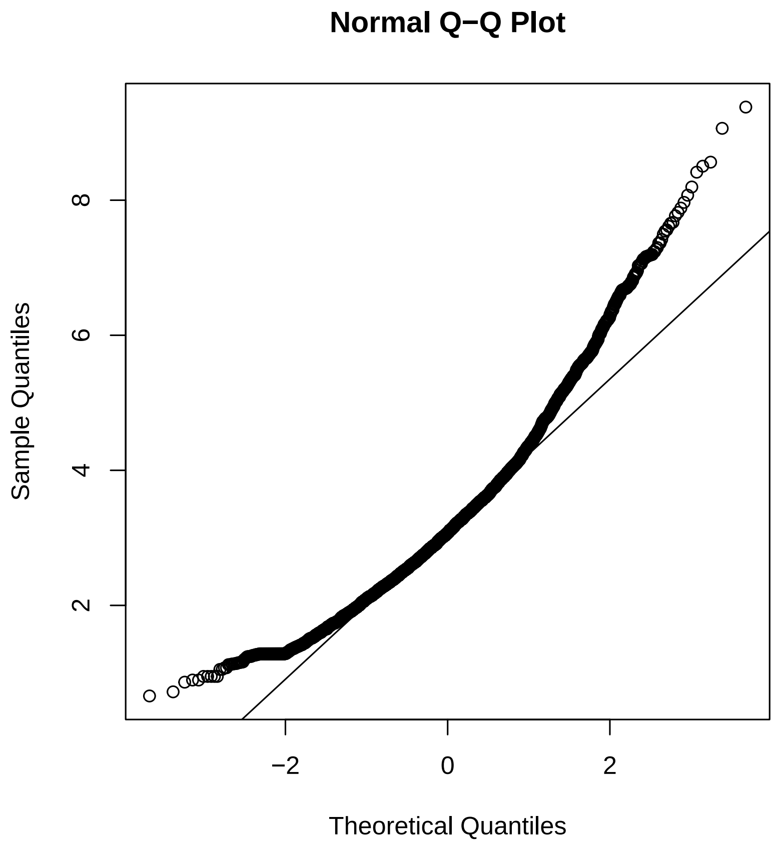
Ambilavent classim with men as target

Mardia's test for evaluate multivariate normality.

```
mardia(db_proc[,c("pp_pm_1", "pp_pm_2", "pp_pm_3", "pp_pm_4",
                  "cc_pm_1", "cc_pm_2", "cc_pm_3", "cc_pm_4",
                  "hc_pm_1", "hc_pm_2", "hc_pm_3", "hc_pm_4")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("pp_pm_1", "pp_pm_2", "pp_pm_3", "pp_pm_4", "cc_pm_1", "cc_pm_2", "cc_pm_3", "cc_pm_4", "hc_pm_1", "hc_pm_2", "hc_pm_3", "hc_pm_4")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 12 b1p = 8.22 skew = 5768.28 with probability <= 0 small sample skew = 5773.03 with probability <= 0 b2p = 234.53 kurtosis = 117.74



with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```
# model
model_cfa <- '
  aci_pp =~ pp_pm_1 + pp_pm_2 + pp_pm_3 + pp_pm_4
  aci_cc =~ cc_pm_1 + cc_pm_2 + cc_pm_3 + cc_pm_4
  aci_hc =~ hc_pm_1 + hc_pm_2 + hc_pm_3 + hc_pm_4
  aci =~ aci_pp + aci_cc + aci_hc '
```

```r
# estimation
m3_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m3_cfa_arg <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 1),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m3_cfa_cl <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 3),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m3_cfa_col <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 4),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m3_cfa_es <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 9),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m3_cfa_mex <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 13),
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

```r
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9
```

```
bind_rows(
  cfa_tab_fit(
    models = list(m2_cfa, m2_cfa_arg, m2_cfa_cl, m2_cfa_col, m2_cfa_es, m2_cfa_mex),
    country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Mé
  )$sum_fit %>%
    mutate(target = "Poor Women")
  ,
  cfa_tab_fit(
    models = list(m3_cfa, m3_cfa_arg, m3_cfa_cl, m3_cfa_col, m3_cfa_es, m3_cfa_mex),
    country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Mé
  )$sum_fit %>%
    mutate(target = "Poor Men")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
    format     = "markdown",
    digits     = 3,
    booktabs   = TRUE,
    col.names  = colnames_fit,
    caption    = NULL
  ) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 8: Summary fit indices of Ambivalent Classism Inventory

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Poor Women	4209	ML	963.662 (51) ***	0.938	0.919	0.065 [0.062-0.069]	0.061	184251.80
	Poor Men	4209	ML	875.132 (51) ***	0.965	0.955	0.062 [0.058-0.066]	0.061	175230.23
Argentina	Poor Women	807	ML	265.228 (51) ***	0.924	0.901	0.072 [0.064-0.081]	0.072	35713.32
	Poor Men	807	ML	295.154 (51) ***	0.945	0.929	0.077 [0.069-0.086]	0.073	34033.94
Chile	Poor Women	883	ML	331.766 (51) ***	0.911	0.885	0.079 [0.071-0.087]	0.076	38590.58
	Poor Men	883	ML	202.945 (51) ***	0.968	0.959	0.058 [0.05-0.067]	0.060	36691.01
Colombia	Poor Women	833	ML	229.327 (51) ***	0.932	0.911	0.065 [0.056-0.073]	0.063	36271.89
	Poor Men	833	ML	208.431 (51) ***	0.962	0.951	0.061 [0.052-0.07]	0.061	34976.60
Spain	Poor Women	835	ML	178.617 (51) ***	0.963	0.952	0.055 [0.046-0.064]	0.057	33998.19
	Poor Men	835	ML	241.732 (51) ***	0.967	0.957	0.067 [0.059-0.076]	0.061	32088.39
México	Poor Women	846	ML	203.834 (51) ***	0.934	0.915	0.06 [0.051-0.068]	0.059	38260.01
	Poor Men	846	ML	237.3 (51) ***	0.957	0.945	0.066 [0.057-0.074]	0.064	36206.58

5.2 Block 2. Gender inequality / Attitudes

5.2.1 Ambivalent sexism

The items to capture ambivalent sexism came from previous research from Rollero et al. (2014) and Rodríguez-Castro et al. (2009). For the SOGEDI study ee included the Ambivalent Sexism Inventory (ASI) and the Ambivalence Toward Men Inventory (AMI), attempting to have a structure similar to that of ambivalent classim scale. We used the short versions of the scales and selected the items that best fit our study. The items are from the adaptation to Spanish.

Paternalism sexism toward women

Descriptive results

```r
describe_kable(db_proc, c("ps_m_1", "ps_m_2", "ps_m_3"))
```

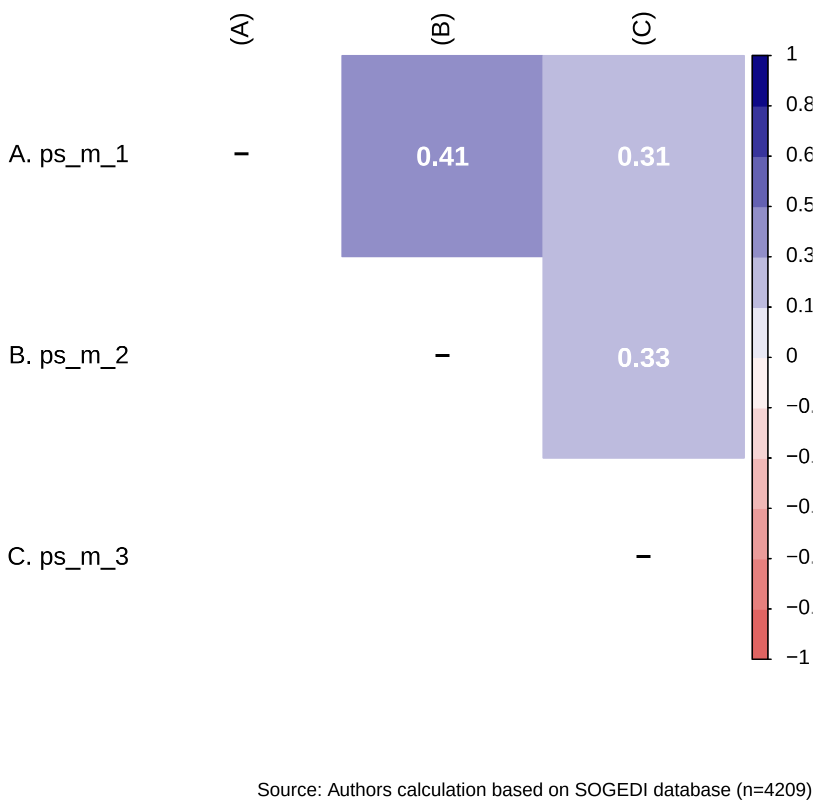
Table 9: Descriptive statistics of Paternalism sexism toward women

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
ps_m_1	1	4209	4.926	1.983	5	5.157	2.965	1	7	6	-0.598	-0.763	0.031
ps_m_2	2	4209	3.480	2.280	4	3.351	4.448	1	7	6	0.284	-1.399	0.035
ps_m_3	3	4209	3.429	1.881	4	3.310	1.483	1	7	6	0.225	-0.937	0.029

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("ps_m_1", "ps_m_2", "ps_m_3")),
      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(caption = paste0(
    "Source: Authors calculation based on SOGEDI",
```

```
    " database (n=", nrow(db_proc), ")"
  ))
```

Figure 4: Correlation matrix of Paternalism sexism toward women



Reliability

```
mi_variable <- "ps_m"
result2 <- alphas(db_proc, c("ps_m_1", "ps_m_2", "ps_m_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.6148687
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.000   4.000   3.945   5.000   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("ps_m_1", "ps_m_2", "ps_m_3")], na.rm =
```

Hostility sexism toward women

Descriptive results

```r
describe_kable(db_proc, c("hs_m_1", "hs_m_2", "hs_m_3"))
```

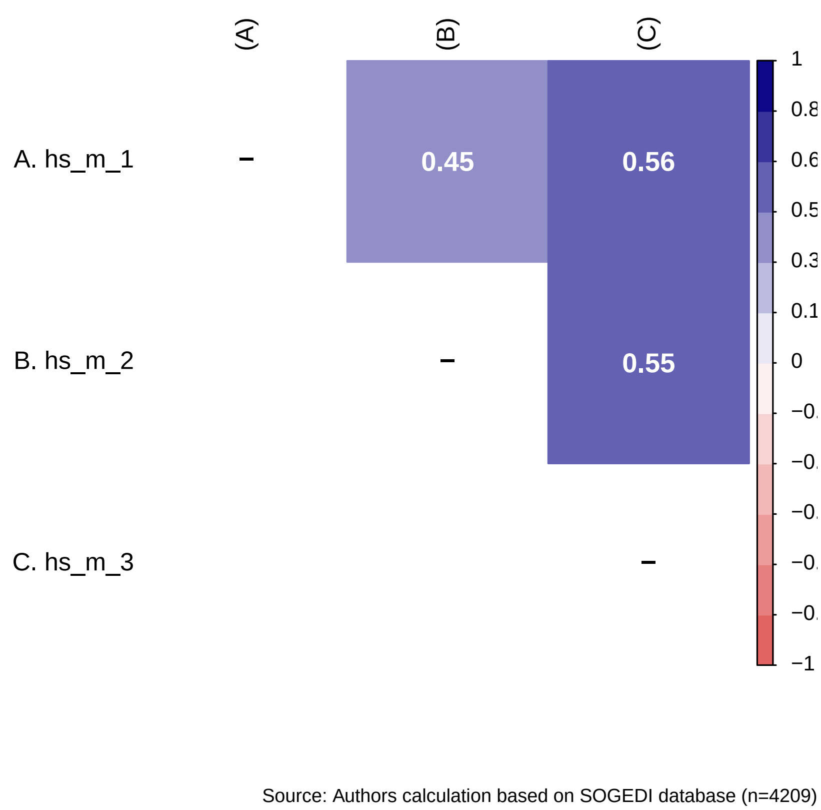
Table 10: Descriptive statistics of Hostility sexism toward women

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
hs_m_1	1	4209	3.370	1.818	4	3.260	1.483	1	7	6	0.234	-0.926	0.028
hs_m_2	2	4209	2.914	1.776	3	2.725	2.965	1	7	6	0.571	-0.675	0.027
hs_m_3	3	4209	3.267	1.958	3	3.109	2.965	1	7	6	0.349	-1.054	0.030

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("hs_m_1", "hs_m_2", "hs_m_3")),
      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(caption = paste0(
    "Source: Authors calculation based on SOGEDI",
    " database (n=", nrow(db_proc), ")"
  ))
```

Figure 5: Correlation matrix of Hostility sexism toward women



Reliability

```
mi_variable <- "hs_m"
result2 <- alphas(db_proc, c("hs_m_1", "hs_m_2", "hs_m_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7658961
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   2.000   3.000   3.184   4.333   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("hs_m_1", "hs_m_2", "hs_m_3")], na.rm =
```

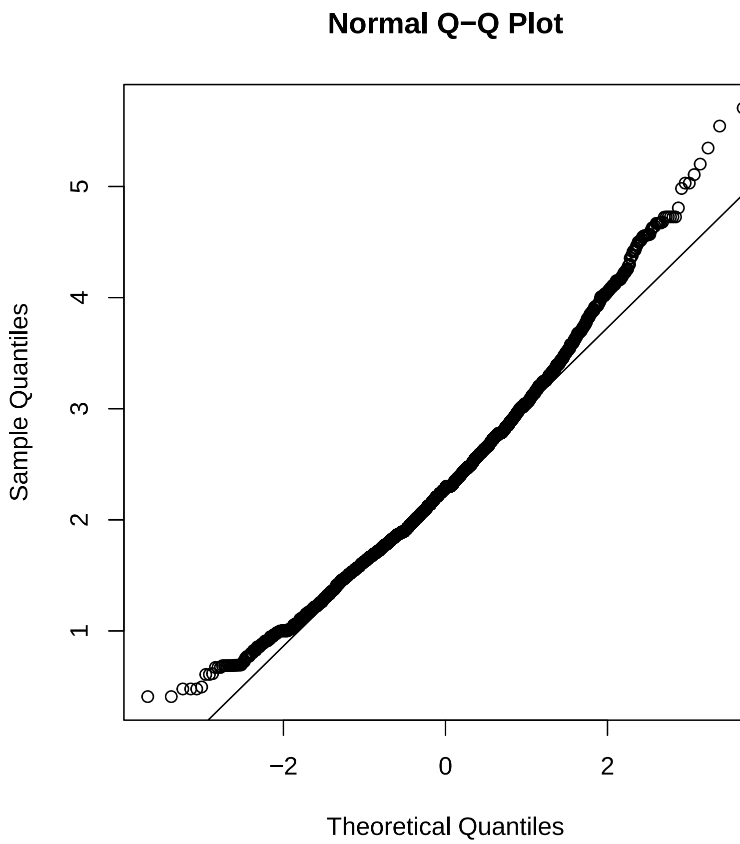
Confirmatory Factor Analysis

Mardia's test for evaluate multivariate normality.

```
mardia(db_proc[,c("ps_m_1", "ps_m_2", "ps_m_3",
                  "hs_m_1", "hs_m_2", "hs_m_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("ps_m_1", "ps_m_2", "ps_m_3", "hs_m_1", "hs_m_2", "hs_m_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 6 b1p = 1.55 skew = 1087.81 with probability <= 0.000000000000000000000000000000000000000000000000000000000000000000000000000000000
small sample skew = 1088.81 with probability <= 0.000000000000000000000000000000000000000000



b2p = 50.82 kurtosis = 9.35 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  psm =~ ps_m_1 + ps_m_2 + ps_m_3
  hsm =~ hs_m_1 + hs_m_2 + hs_m_3
  asi =~ psm + hsm '

# estimation
m4_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

```
m4_cfa_arg <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 1),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m4_cfa_cl <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 3),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m4_cfa_col <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 4),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m4_cfa_es <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 9),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m4_cfa_mex <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 13),
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

```
cfa_tab_fit(
  models = list(m4_cfa, m4_cfa_arg, m4_cfa_cl, m4_cfa_col, m4_cfa_es, m4_cfa_mex),
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$fit_table
```

Table 11: Summary fit indices of Ambivalent sexism toward women

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	76.711 (7) ***	0.987	0.972	0.049 [0.039-0.059]	0.025	100051.14
Argentina	807	ML	6.668 (7)	1.000	1.001	0 [0-0.042]	0.015	19274.62
Chile	883	ML	34.958 (7) ***	0.972	0.941	0.067 [0.046-0.09]	0.032	21052.17
Colombia	833	ML	24.371 (7) ***	0.979	0.955	0.055 [0.032-0.079]	0.034	19686.31
Spain	835	ML	22.911 (7) **	0.988	0.974	0.052 [0.029-0.077]	0.037	18591.20
México	846	ML	35.833 (7) ***	0.964	0.923	0.07 [0.048-0.093]	0.041	20419.26

5.2.2 Perception of gender inequality

We selected six items from the original scale developed by Schwartz-Salazar et al. (2024) that have several subdimensions. The reduced scale has not being published before so we will explore the factor structure of this four items.

Descriptive results

```
describe_kable(db_proc, c("gen_in_1", "gen_in_2", "gen_in_3", "gen_in_4", "gen_in_5",
```

Table 12: Descriptive statistics of Perception of gender inequality

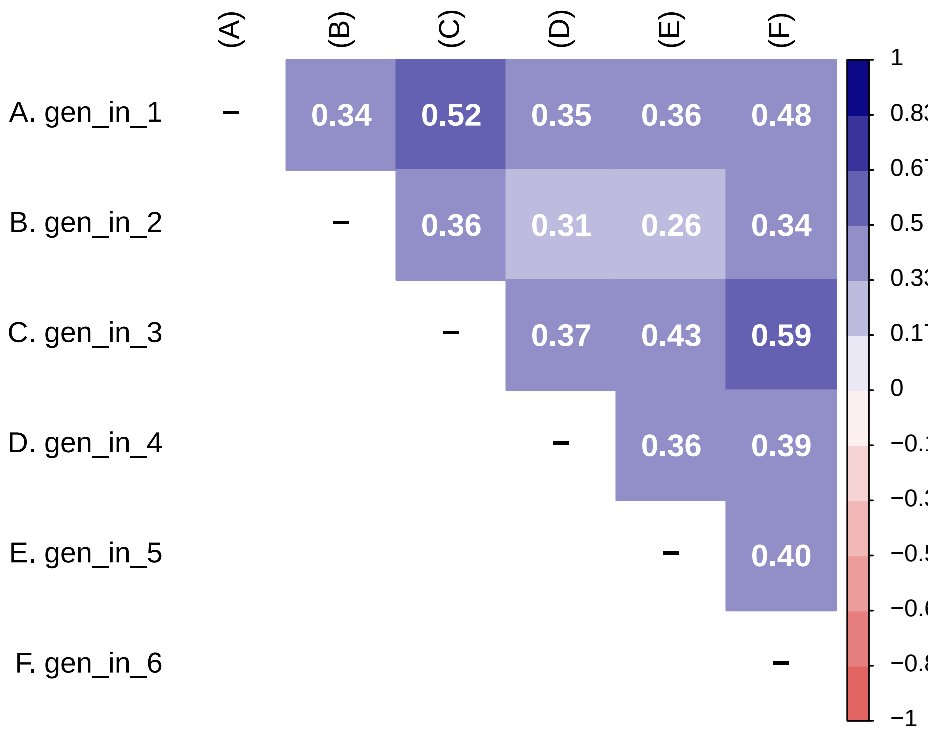
	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
gen_in_1	1	4209	5.345	1.792	6	5.631	1.483	1	7	6	-0.995	0.060	0.028
gen_in_2	2	4209	5.553	1.588	6	5.814	1.483	1	7	6	-1.152	0.773	0.024
gen_in_3	3	4209	4.694	1.939	5	4.868	1.483	1	7	6	-0.521	-0.801	0.030
gen_in_4	4	4209	4.404	2.061	5	4.505	2.965	1	7	6	-0.358	-1.093	0.032

Table 12: Descriptive statistics of Perception of gender inequality

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
gen_in_5	5	4209	3.941	2.033	4	3.927	2.965	1	7	6	-0.046	-1.160	0.031
gen_in_6	6	4209	4.440	1.931	5	4.549	1.483	1	7	6	-0.400	-0.877	0.030

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("gen_in_1", "gen_in_2", "gen_in_3", "gen_in_4", "gen
      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(caption = paste0(
    "Source: Authors calculation based on SOGEDI",
    " database (n=", nrow(db_proc), ")"
  ))
```

Figure 6: Correlation matrix of Perception of gender inequality



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

Reliability

```
mi_variable <- "gen_in"
result2 <- alphas(db_proc, c("gen_in_1", "gen_in_2", "gen_in_3", "gen_in_4", "gen_in_5

result2$raw_alpha
```

```
[1] 0.7923002
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.833   4.833   4.730   5.667   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("gen_in_1", "gen_in_2", "gen_in_3", "ge
```

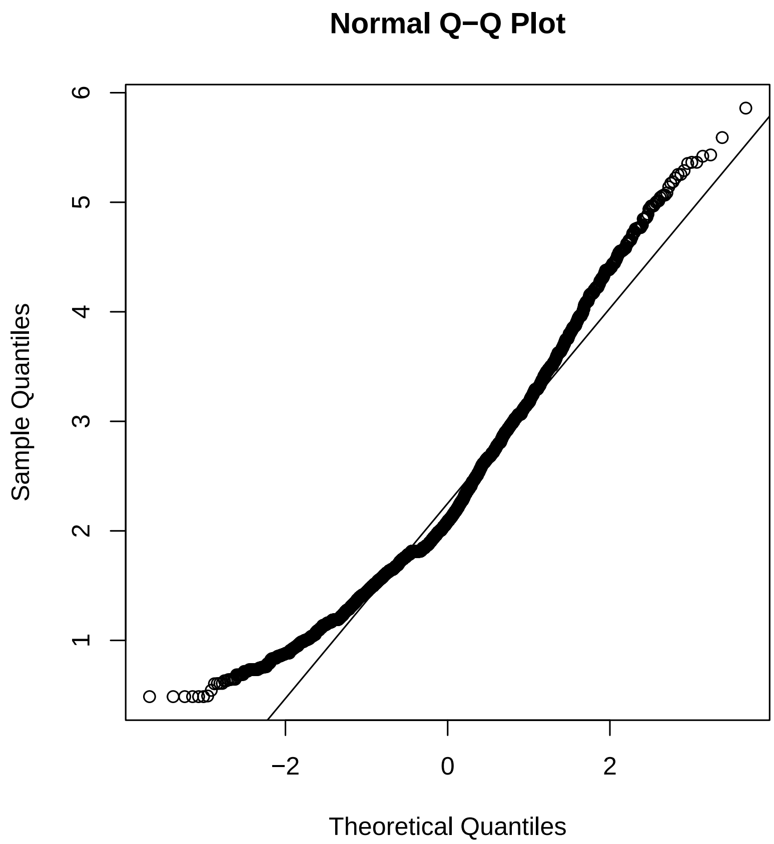
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality.

```r
mardia(db_proc[,c("gen_in_1", "gen_in_2", "gen_in_3",
                  "gen_in_4", "gen_in_5", "gen_in_6")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("gen_in_1", "gen_in_2", "gen_in_3", "gen_in_4", "gen_in_5", "gen_in_6")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 6 b1p = 3.68 skew = 2584.66 with probability <= 0 small sample skew = 2587.03 with probability <= 0 b2p = 58.55 kurtosis = 34.94 with



probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- ' gender_inquality =~ gen_in_1 + gen_in_2 + gen_in_3 + gen_in_4 + gen_in_

# estimation
m5_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m5_cfa_arg <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 1),
```

```r
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m5_cfa_cl <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 3),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m5_cfa_col <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 4),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m5_cfa_es <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 9),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m5_cfa_mex <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 13),
               estimator = "MLR",
               ordered = F,
               std.lv = F)
```

```r
cfa_tab_fit(
  models = list(m5_cfa, m5_cfa_arg, m5_cfa_cl, m5_cfa_col, m5_cfa_es, m5_cfa_mex),
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$fit_table
```

Table 13: Summary fit indices of Perception of gender inequality

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	104.751 (9) ***	0.985	0.975	0.05 [0.042-0.059]	0.022	97265.33

Table 13: Summary fit indices of Perception of gender inequality

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Argentina	807	ML	39.691 (9) ***	0.975	0.958	0.065 [0.045-0.086]	0.033	19036.01
Chile	883	ML	50.238 (9) ***	0.965	0.941	0.072 [0.053-0.092]	0.036	20337.77
Colombia	833	ML	28.297 (9) ***	0.982	0.970	0.051 [0.03-0.072]	0.027	19551.93
Spain	835	ML	46.197 (9) ***	0.981	0.969	0.07 [0.051-0.091]	0.028	18118.03
México	846	ML	21.14 (9) *	0.990	0.984	0.04 [0.018-0.062]	0.021	19692.44

5.2.3 Belief in sexism shift

The items to capture belief in sexism shift came from previous research from Zehnter et al. (2021). We translated four items from the original scale, adapting them to our context and objectives. These items are the ones that saturate the most in the scale across various studies.

Descriptive results

```
describe_kable(db_proc, c("shif_1", "shif_2", "shif_3"))
```

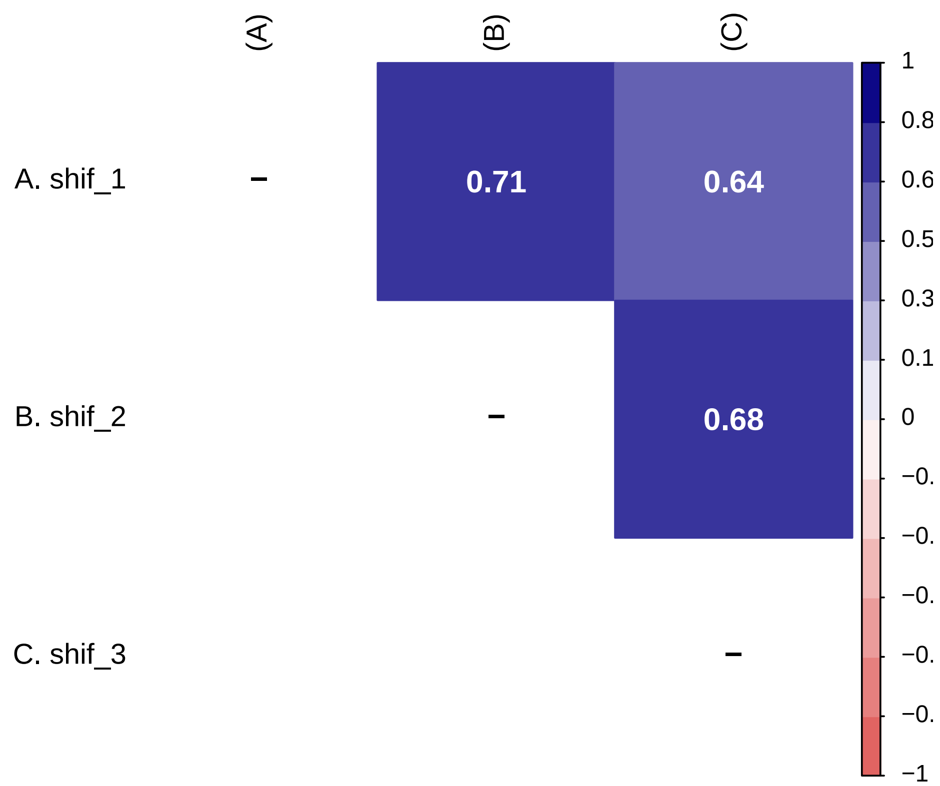
Table 14: Descriptive statistics of Belief in sexism shift

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
shif_1	1	4209	3.507	1.994	4	3.384	2.965	1	7	6	0.211	-1.123	0.031
shif_2	2	4209	3.192	1.995	3	3.004	2.965	1	7	6	0.428	-1.019	0.031
shif_3	3	4209	3.286	2.112	3	3.107	2.965	1	7	6	0.371	-1.213	0.033

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("shif_1", "shif_2", "shif_3")),
      method = "color",
      type = "upper",
```

```r
    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(caption = paste0(
  "Source: Authors calculation based on SOGEDI",
  " database (n=", nrow(db_proc), ")"
))
```

Figure 7: Correlation matrix of Belief in sexism shift



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

Reliability

```
mi_variable <- "shif"
result2 <- alphas(db_proc, c("shif_1", "shif_2", "shif_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8612019
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.667   3.333   3.328   4.667   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("shif_1", "shif_2", "shif_3")], na.rm =
```

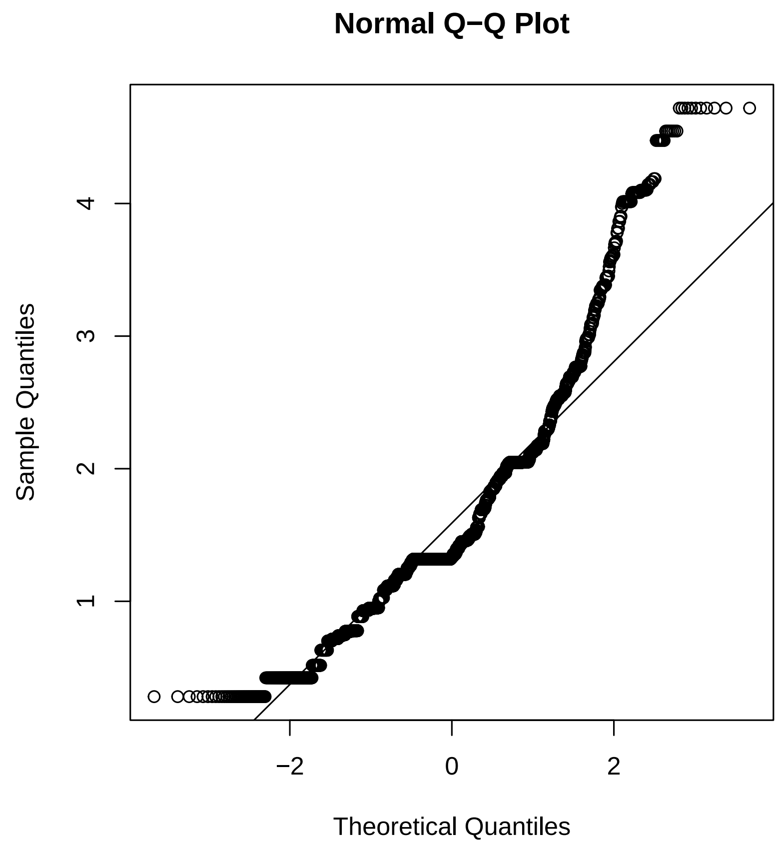
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality.

```
mardia(db_proc[,c("shif_1", "shif_2", "shif_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("shif_1", "shif_2", "shif_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 3 b1p = 0.37 skew = 258.14 with probability <= 0.000000000000000000000000000000000000000000000011 small sample skew = 258.42 with probability <= 0.0000000000000000000000000000000000000000000000092 b2p



= 18.61 kurtosis = 21.39 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- ' shif_sexism =~ shif_1 + shif_2 + shif_3 '

# estimation
m6_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m6_cfa_arg <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 1),
```

```
                estimator = "MLR",
                ordered = F,
                std.lv = F)

m6_cfa_cl <- cfa(model = model_cfa,
                data = subset(db_proc, country_residence_recoded == 3),
                estimator = "MLR",
                ordered = F,
                std.lv = F)

m6_cfa_col <- cfa(model = model_cfa,
                data = subset(db_proc, country_residence_recoded == 4),
                estimator = "MLR",
                ordered = F,
                std.lv = F)

m6_cfa_es <- cfa(model = model_cfa,
                data = subset(db_proc, country_residence_recoded == 9),
                estimator = "MLR",
                ordered = F,
                std.lv = F)

m6_cfa_mex <- cfa(model = model_cfa,
                data = subset(db_proc, country_residence_recoded == 13),
                estimator = "MLR",
                ordered = F,
                std.lv = F)
```

```
cfa_tab_fit(
  models = list(m6_cfa, m6_cfa_arg, m6_cfa_cl, m6_cfa_col, m6_cfa_es, m6_cfa_mex),
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$fit_table
```

Table 15: Summary fit indices of Belief in sexism shift

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	0 (0)	1	1	0 [0-0]	0	47815.314

Table 15: Summary fit indices of Belief in sexism shift

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Argentina	807	ML	0 (0)	1	1	0 [0-0]	0	9215.297
Chile	883	ML	0 (0)	1	1	0 [0-0]	0	9970.867
Colombia	833	ML	0 (0)	1	1	0 [0-0]	0	9605.729
Spain	835	ML	0 (0)	1	1	0 [0-0]	0	8687.609
México	846	ML	0 (0)	1	1	0 [0-0]	0	9885.223

5.2.4 Feminism identification

The item to capture feminism identification came from previous research from Estevan-Reina et al. (2020). We translated the item from the original scale, adapting to our context and objectives.

Descriptive analysis

```
psych::describe(db_proc$femi) %>%
    kableExtra::kable(format = "markdown", digits = 3)
```

Table 16: Descriptive statistics of Feminism identification

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	4209	3.423	2.112	4	3.423	2.965	1	7	6	0.258	-1.238	0.033

5.2.5 Gender inequality justification

The item to capture feminism identification came from previous research from Jost & Kay (2005). We translated the item from the original scale, adapting to our context and objectives.

```
psych::describe(db_proc$jus_gen) %>%
    kableExtra::kable(format = "markdown", digits = 3)
```

Table 17: Descriptive statistics of Gender inequality justification

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	4209	2.774	1.747	2	2.774	1.483	1	7	6	0.735	-0.36	0.027

5.2.6 Gender inequality collective action

The item to capture gender inequality collective action was created by the project team.

```
psych::describe(db_proc$co_gen) %>%
    kableExtra::kable(format = "markdown", digits = 3)
```

Table 18: Descriptive statistics of Gender inequality collective action

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	4209	4.365	2.051	4	4.365	2.965	1	7	6	-0.275	-1.107	0.032

5.2.7 Perception of gender competition

The item to capture gender inequality collective action was created by the project team.

```
psych::describe(db_proc$gen_compe) %>%
    kableExtra::kable(format = "markdown", digits = 3)
```

Table 19: Descriptive statistics of Perception of gender competition

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	4209	4.592	1.611	5	4.592	1.483	1	7	6	-0.38	-0.174	0.025

5.3 Block 3. Contacts and rates

5.3.1 Gendered poverty rates

The items to capture gender poverty rates was inspired by the research of Kuo et al. (2020).

```r
describe_kable(db_proc, c("ge_ra_wo", "ge_ra_me"))
```

Table 20: Descriptive statistics of Gendered poverty rates

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
ge_ra_wo	1	4209	52.366	12.893	50	52.832	14.826	5	100	95	-0.289	0.343	0.199
ge_ra_me	2	4209	47.634	12.893	50	47.168	14.826	0	95	95	0.289	0.343	0.199

5.3.2 Intergroup contacts: quantity of contacts

The variables used to capture this inter group contacts was derived from previous research from Vargas et al. (2023) and Vázquez et al. (2023). The wording of the items is based on the COES longitudinal survey, incorporating some supplementary information from Vargas et al. (2023) regarding the places where contact can occur.

```r
describe_kable(db_proc, c("quan_pw", "quan_pm", "quan_rw", "quan_rm"))
```

Table 21: Descriptive statistics of Intergroup contacts: quantity of contacts

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
quan_pw	1	4209	4.162	1.799	4	4.164	1.483	1	7	6	0.082	-0.937	0.028
quan_pm	2	4209	4.166	1.824	4	4.175	1.483	1	7	6	0.063	-0.978	0.028
quan_rw	3	4209	4.066	1.732	4	4.065	1.483	1	7	6	-0.019	-0.812	0.027
quan_rm	4	4209	4.096	1.762	4	4.105	1.483	1	7	6	-0.054	-0.876	0.027

5.3.3 Intergroup contacts: friendship

The variables used to capture this inter group friendship was developed by the project team.

```r
describe_kable(db_proc, c("fri_pw", "fri_pm", "fri_rw", "fri_rm"))
```

Table 22: Descriptive statistics of Intergroup contacts: friendship

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
fri_pw	1	4209	2.800	1.732	2	2.598	1.483	1	7	6	0.719	-0.372	0.027
fri_pm	2	4209	2.790	1.737	2	2.581	1.483	1	7	6	0.730	-0.364	0.027
fri_rw	3	4209	3.587	1.711	4	3.545	1.483	1	7	6	0.046	-0.863	0.026
fri_rm	4	4209	3.601	1.749	4	3.555	1.483	1	7	6	0.066	-0.901	0.027

5.3.4 Intergroup contacts: quality of contacts

The variables used to capture this inter group contacts was derived from previous research from Vázquez et al. (2023) and from Roberto Gonzalez FONDECYT dataset.

```r
describe_kable(db_proc, c("qual_pw", "qual_pm", "qual_rw", "qual_rm"))
```

Table 23: Descriptive statistics of Intergroup contacts: quality of contacts

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
qual_pw	1	4209	4.671	1.378	4	4.679	1.483	1	7	6	-0.044	-0.185	0.021
qual_pm	2	4209	4.445	1.415	4	4.447	1.483	1	7	6	-0.043	-0.097	0.022
qual_rw	3	4209	4.174	1.410	4	4.187	1.483	1	7	6	-0.052	-0.083	0.022
qual_rm	4	4209	4.148	1.440	4	4.166	1.483	1	7	6	-0.092	-0.131	0.022

5.3.5 Perception of social mobility

For social mobility perceptions, we selected the items from the scale developed by Matamoros-Lima et al. (2023) that better suits our context of study having in mind the survey space limitations.

Descriptive results

```
describe_kable(db_proc, c("mobi_up_1", "mobi_up_2", "mobi_up_3", "mobi_down_1", "mobi_
```

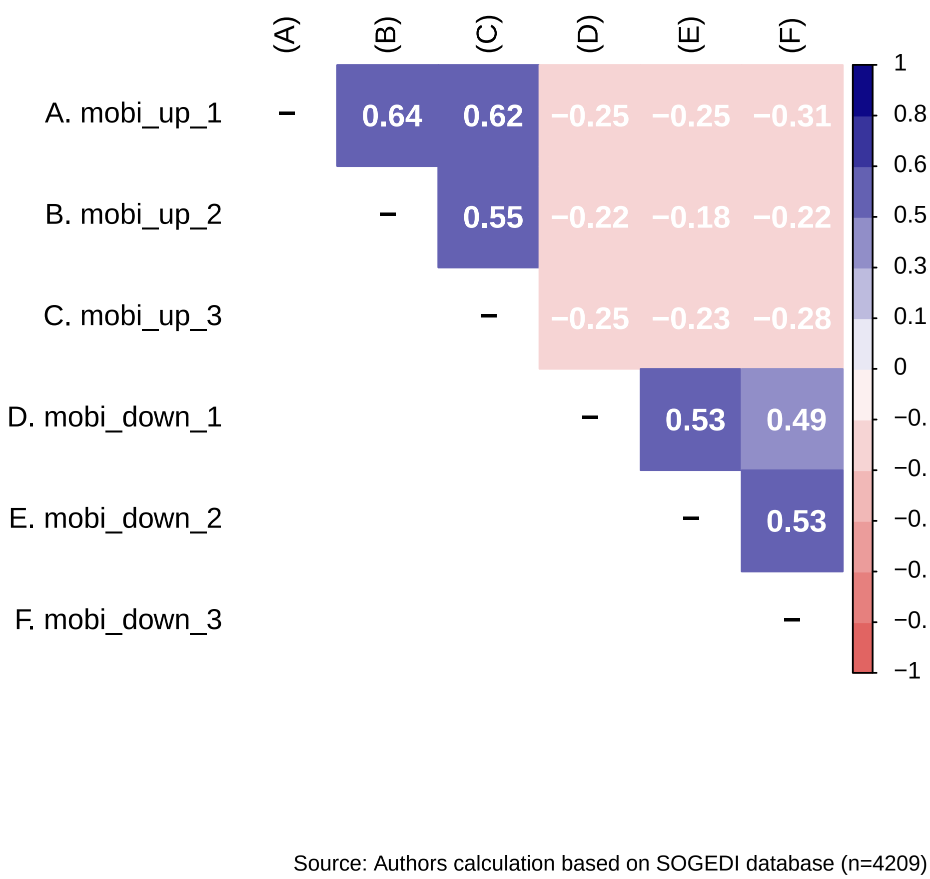
Table 24: Descriptive statistics of Perception of social mobility

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
mobi_up_1	1	4209	4.285	1.525	4	4.321	1.483	1	7	6	-0.222	-0.367	0.024
mobi_up_2	2	4209	3.941	1.531	4	3.966	1.483	1	7	6	-0.130	-0.378	0.024
mobi_up_3	3	4209	4.365	1.545	4	4.421	1.483	1	7	6	-0.332	-0.270	0.024
mobi_down_1	4	4209	4.133	1.663	4	4.126	1.483	1	7	6	0.020	-0.672	0.026
mobi_down_2	5	4209	3.772	1.593	4	3.740	1.483	1	7	6	0.157	-0.495	0.025
mobi_down_3	6	4209	3.491	1.557	3	3.431	1.483	1	7	6	0.268	-0.418	0.024

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("mobi_up_1", "mobi_up_2", "mobi_up_3", "mobi_down_1"
      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(caption = paste0(
    "Source: Authors calculation based on SOGEDI",
    " database (n=", nrow(db_proc), ")"
  ))
```

Figure 8: Correlation matrixes of Perception of social mobility



Reliability

```
mi_variable <- "ascenmobi"
result2 <- alphas(db_proc, c("mobi_up_1", "mobi_up_2", "mobi_up_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8200618
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   3.333   4.333   4.197   5.000   7.000
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("mobi_up_1", "mobi_up_2", "mobi_up_3")]
```

```
mi_variable <- "descenmobi"
result3 <- alphas(db_proc, c("mobi_down_1", "mobi_down_2", "mobi_down_3"), mi_variable

result3$raw_alpha
```

```
[1] 0.7613283
```

```
result3$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   3.000   3.667   3.799   4.667   7.000
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("mobi_down_1", "mobi_down_2", "mobi_dow
```

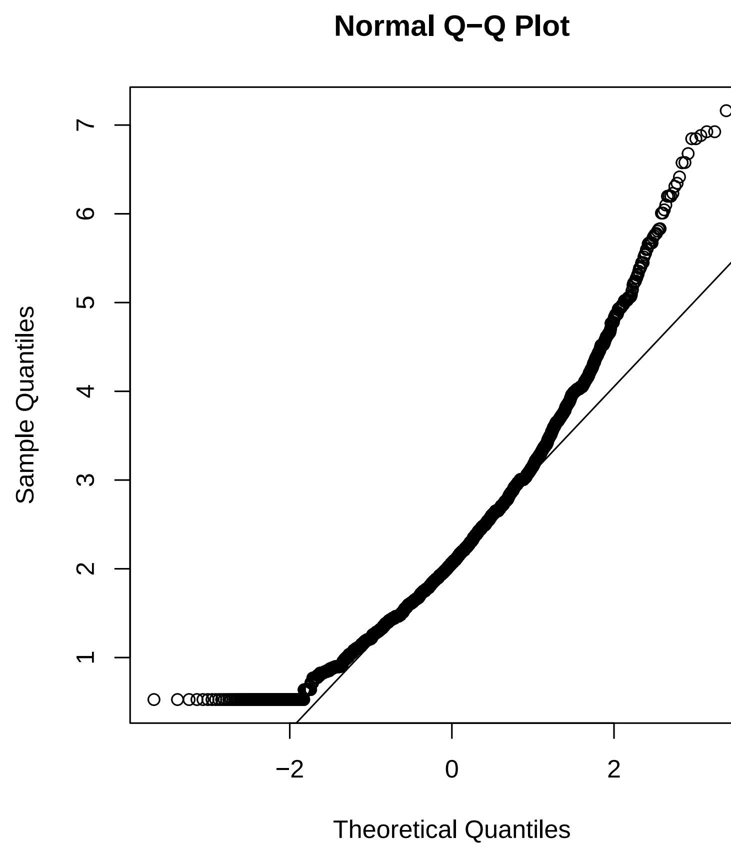
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality.

```r
mardia(db_proc[,c("mobi_up_1", "mobi_up_2", "mobi_up_3",
                   "mobi_down_1", "mobi_down_2", "mobi_down_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("mobi_up_1", "mobi_up_2", "mobi_up_3", "mobi_down_1", "mobi_down_2", "mobi_down_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 6 b1p = 1.54 skew = 1082.29 with probability <= 0.0000000000000000000000000000000000000000000000000000000000000000000000000000000000000000000
small sample skew = 1083.28 with probability <= 0.00000000000000000000000000000000000000000000000



b2p = 70.82 kurtosis = 75.56 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```r
# model
model_cfa <- '
  ascen_mobi =~ mobi_up_1 + mobi_up_2 + mobi_up_3
  descen_mobi =~ mobi_down_1 + mobi_down_2 + mobi_down_3
   '

# estimation
m7_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m7_cfa_arg <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 1),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m7_cfa_cl <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 3),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m7_cfa_col <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 4),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m7_cfa_es <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 9),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m7_cfa_mex <- cfa(model = model_cfa,
              data = subset(db_proc, country_residence_recoded == 13),
              estimator = "MLR",
```

```
              ordered = F,
              std.lv = F)
```

```
cfa_tab_fit(
  models = list(m7_cfa, m7_cfa_arg, m7_cfa_cl, m7_cfa_col, m7_cfa_es, m7_cfa_mex),
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$fit_table
```

Table 25: Summary fit indices of Social mobility

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	75.006 (8) ***	0.992	0.985	0.045 [0.036-0.054]	0.022	86196.60
Argentina	807	ML	14.709 (8) .	0.996	0.992	0.032 [0-0.058]	0.022	16519.25
Chile	883	ML	32.329 (8) ***	0.982	0.966	0.059 [0.038-0.08]	0.038	17606.56
Colombia	833	ML	9.724 (8)	0.999	0.998	0.016 [0-0.046]	0.020	17128.96
Spain	835	ML	17.68 (8) *	0.995	0.991	0.038 [0.013-0.062]	0.020	15950.95
México	846	ML	39.068 (8) ***	0.974	0.951	0.068 [0.047-0.09]	0.034	17776.29

5.4 Block 4. Stereotypes

5.4.1 Stereotype content model: inmmorality

We included the immorality scale in an exploratory manner. The items are form the published article from Sánchez-Castelló et al. (2022).

Descriptive analysis

```
db_proc <- db_proc %>%
  mutate(condi_gender = if_else(condi_gender == 0, "Men", "Women"),
         condi_class = if_else(condi_class == 0, "Poor", "Rich")) %>%
  rowwise() %>%
```

```r
  mutate(target = interaction(condi_class, condi_gender)) %>%
  ungroup()

db_rm <- subset(db_proc, target == "Rich.Men")
db_pm <- subset(db_proc, target == "Poor.Men")
db_rw <- subset(db_proc, target == "Rich.Women")
db_pw <- subset(db_proc, target == "Poor.Women")

bind_rows(
psych::describe(db_rm[,c("inm_1", "inm_2", "inm_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("inm_1", "inm_2", "inm_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("inm_1", "inm_2", "inm_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("inm_1", "inm_2", "inm_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("inm_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 26: Descriptive statistics of Inmmorality

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	inm_1	1043	4.189	1.525	4	4.206	1.483	1	7	6	-0.122	-0.346	0.047
	inm_2	1043	3.940	1.480	4	3.925	1.483	1	7	6	0.054	-0.268	0.046

Table 26: Descriptive statistics of Inmmorality

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
	inm_3	1043	4.095	1.570	4	4.117	1.483	1	7	6	-0.127	-0.428	0.049
Poor Men	inm_1	1058	3.806	1.481	4	3.811	1.483	1	7	6	-0.057	-0.489	0.046
	inm_2	1058	3.317	1.482	3	3.278	1.483	1	7	6	0.164	-0.503	0.046
	inm_3	1058	3.638	1.525	4	3.636	1.483	1	7	6	0.007	-0.589	0.047
Rich Women	inm_1	1056	3.934	1.576	4	3.947	1.483	1	7	6	-0.058	-0.588	0.048
	inm_2	1056	3.689	1.569	4	3.676	1.483	1	7	6	0.082	-0.520	0.048
	inm_3	1056	3.751	1.674	4	3.723	1.483	1	7	6	0.109	-0.678	0.052
Poor Women	inm_1	1052	3.396	1.471	4	3.381	1.483	1	7	6	0.104	-0.639	0.045
	inm_2	1052	2.769	1.390	3	2.677	1.483	1	7	6	0.457	-0.287	0.043
	inm_3	1052	3.021	1.480	3	2.943	1.483	1	7	6	0.330	-0.513	0.046

```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rm, c("inm_1", "inm_2", "inm_3")),
      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"
```

```r
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pm, c("inm_1", "inm_2", "inm_3")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rw, c("inm_1", "inm_2", "inm_3")),
      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"
    )
```

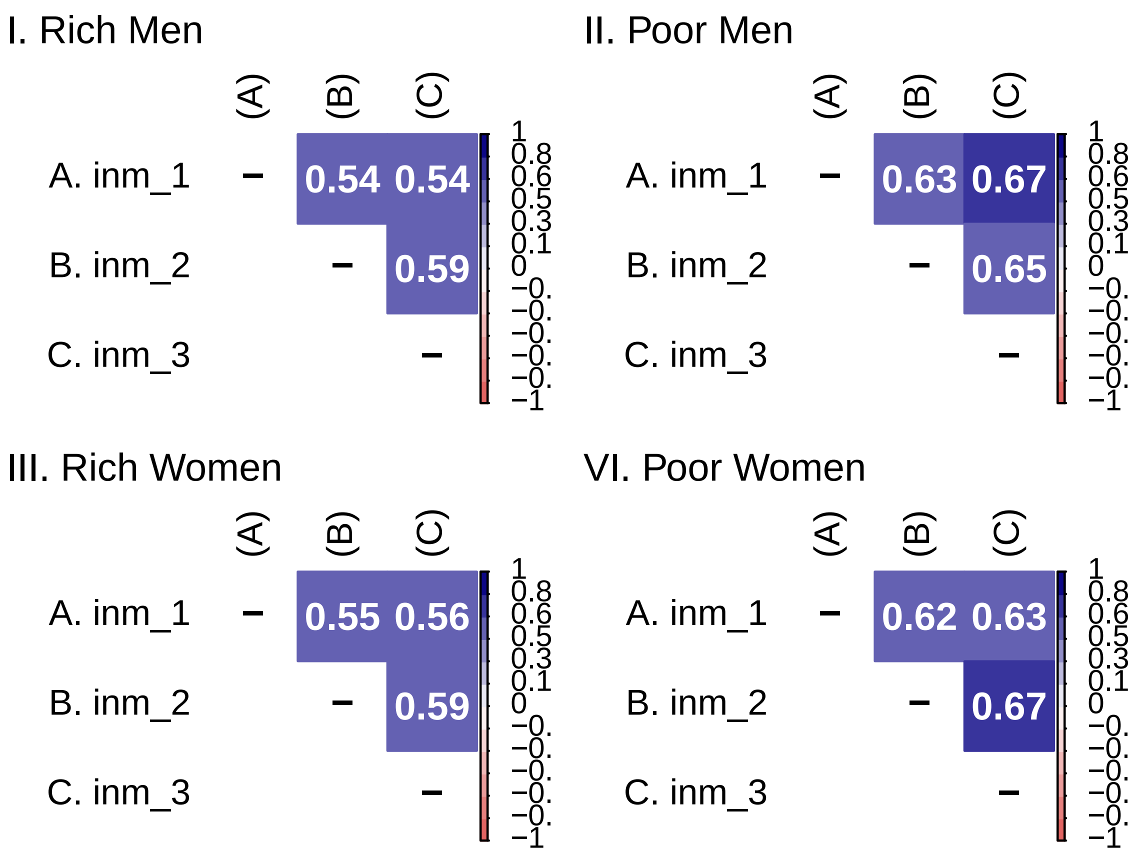
```r
  ) + labs(title = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pw, c("inm_1", "inm_2", "inm_3")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 9: Correlation matrix of Inmmorality



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

Reliability

```r
mi_variable <- "inm"
result2 <- alphas(db_proc, c("inm_1", "inm_2", "inm_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.83072
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   2.667   3.667   3.628   4.333   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("inm_1", "inm_2", "inm_3")], na.rm = TR
```

Confirmatory factor analysis

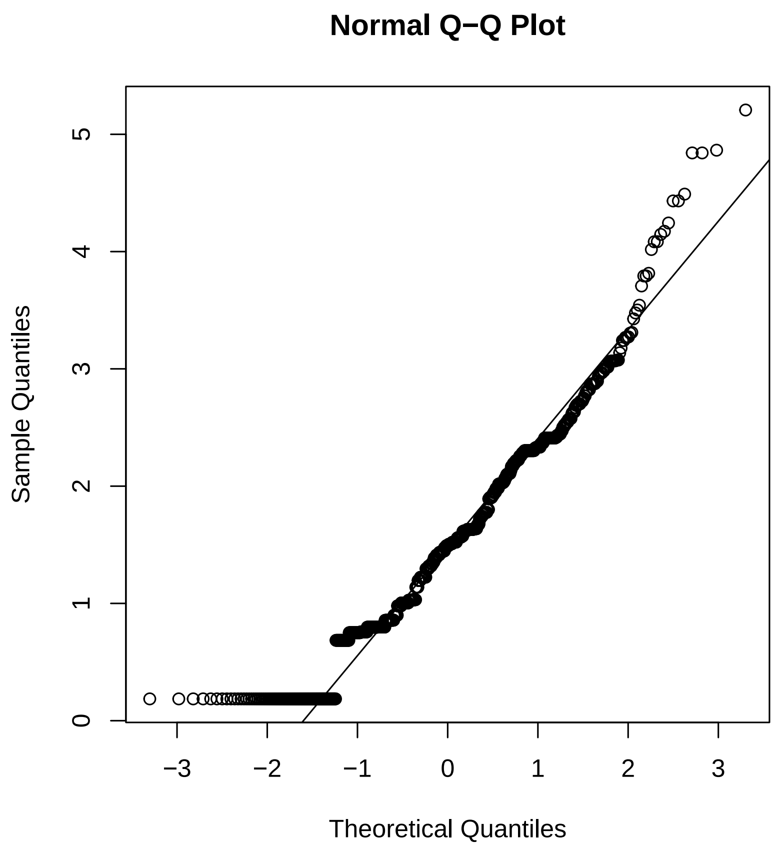
Mardia's test for evaluate multivariate normality for each target.

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```r
# model
model_cfa <- '
  inmorality =~ inm_1 + inm_2 + inm_3
   '

# estimation
# overall
m8_cfa_rm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m8_cfa_pm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m8_cfa_rw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
```

Table 27: Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 0.1 skew = 17.66 with probability <= 0.061 small sample skew = 17.73 with probability <= 0.06 b2p = 19.15 kurtosis = 12.22 with probability <= 0

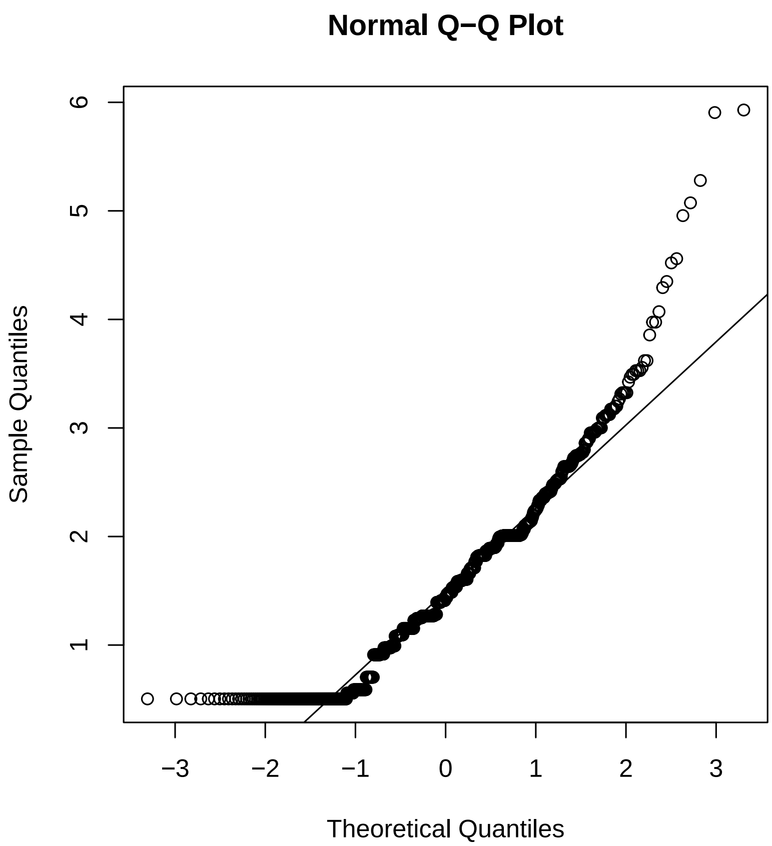
```
mardia(db_rm[,c("inm_1", "inm_2", "inm_3")],
       na.rm = T, plot=T)
```



Call: mardia(x = db_rm[, c("inm_1", "inm_2", "inm_3")], na.rm = T, plot = T)

Table 28: Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1058 num.vars = 3 b1p = 0.35 skew = 61.86 with probability <= 0.0000000016 small sample skew = 62.12 with probability <= 0.0000000014 b2p = 20.38 kurtosis = 15.97 with probability <= 0

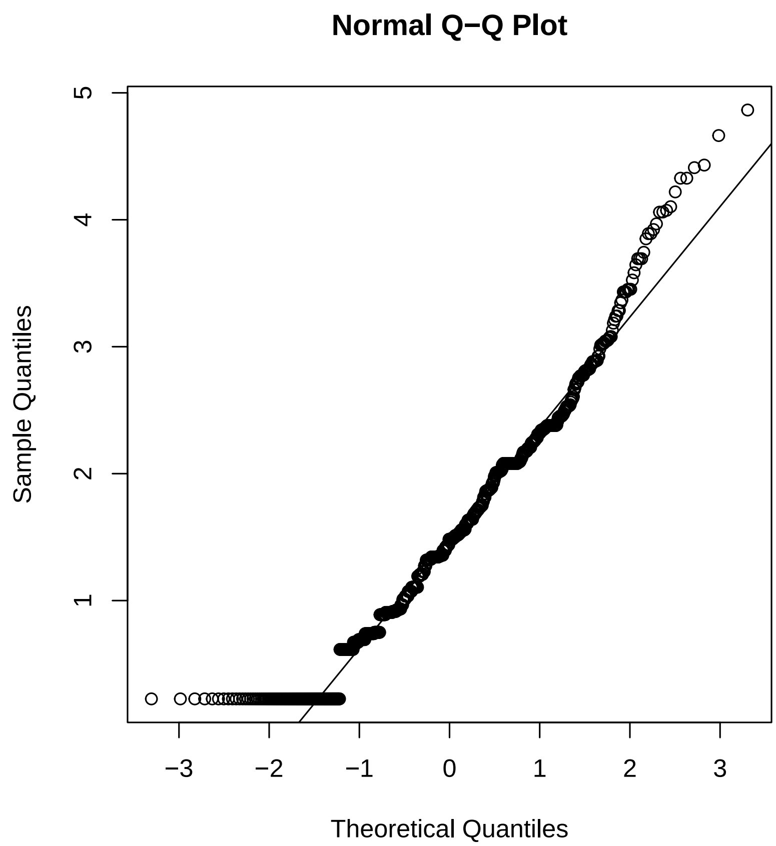
```
mardia(db_pm[,c("inm_1", "inm_2", "inm_3")],
       na.rm = T, plot=T)
```



Call: mardia(x = db_pm[, c("inm_1", "inm_2", "inm_3")], na.rm = T, plot = T)

Table 29: Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1056 num.vars = 3 b1p = 0.22 skew = 38.2 with probability <= 0.000035 small sample skew = 38.37 with probability <= 0.000033 b2p = 18.82 kurtosis = 11.32 with probability <= 0

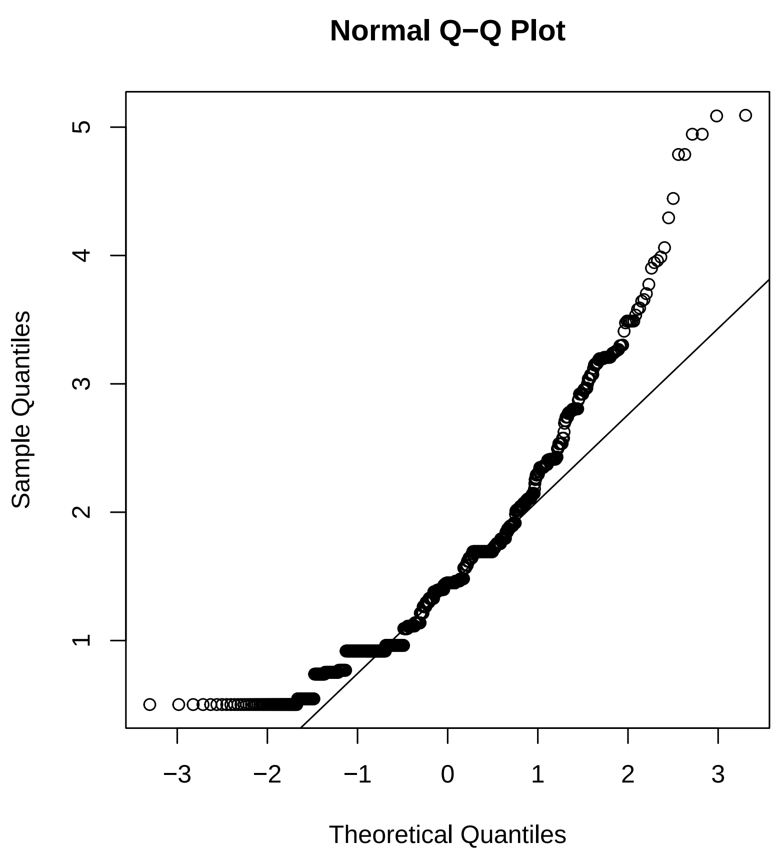
```
mardia(db_rw[,c("inm_1", "inm_2", "inm_3")],
       na.rm = T, plot=T)
```



Call: mardia(x = db_rw[, c("inm_1", "inm_2", "inm_3")], na.rm = T, plot = T)

Table 30: Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1052 num.vars = 3 b1p = 0.94 skew = 164.5 with probability <= 0.000000000000000000000000000038 small sample skew = 165.21 with probability <= 0.000000000000000000000000000027 b2p = 19.65 kurtosis = 13.78 with probability <= 0

```
mardia(db_pw[,c("inm_1", "inm_2", "inm_3")],
       na.rm = T, plot=T)
```



Call: mardia(x = db_pw[, c("inm_1", "inm_2", "inm_3")], na.rm = T, plot = T)

```
               ordered = F,
               std.lv = F)

m8_cfa_pw <- cfa(model = model_cfa,
               data = subset(db_proc, target == "Poor.Women"),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

# per country
db_proc$group <- interaction(db_proc$natio_recoded, db_proc$target)

# argentina
m8_cfa_rm_arg <- cfa(model = model_cfa,
                  data = subset(db_proc, group == "1.Rich.Men"),
                  estimator = "MLR",
                  ordered = F,
                  std.lv = F)

m8_cfa_pm_arg <- cfa(model = model_cfa,
                  data = subset(db_proc, group == "1.Poor.Men"),
                  estimator = "MLR",
                  ordered = F,
                  std.lv = F)

m8_cfa_rw_arg <- cfa(model = model_cfa,
                  data = subset(db_proc, group == "1.Rich.Women"),
                  estimator = "MLR",
                  ordered = F,
                  std.lv = F)

m8_cfa_pw_arg <- cfa(model = model_cfa,
                  data = subset(db_proc, group == "1.Poor.Women"),
                  estimator = "MLR",
                  ordered = F,
                  std.lv = F)

# chile
m8_cfa_rm_cl <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "3.Rich.Men"),
```

```
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_pm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_pw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia
m8_cfa_rm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_pm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_rw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```
m8_cfa_pw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# españa
m8_cfa_rm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_pm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_rw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_pw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# mexico
m8_cfa_rm_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m8_cfa_pm_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Poor.Men"),
```

```
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m8_cfa_rw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m8_cfa_pw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Poor.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)
```

```
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m8_cfa_rm, m8_cfa_rm_arg, m8_cfa_rm_cl, m8_cfa_rm_col, m8_cfa_rm_esp,
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Men")
,
cfa_tab_fit(
  models = list(m8_cfa_pm, m8_cfa_pm_arg, m8_cfa_pm_cl, m8_cfa_pm_col, m8_cfa_pm_esp,
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Men")
,
cfa_tab_fit(
  models = list(m8_cfa_rw, m8_cfa_rw_arg, m8_cfa_rw_cl, m8_cfa_rw_col, m8_cfa_rw_esp,
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
,
cfa_tab_fit(
  models = list(m8_cfa_pw, m8_cfa_pw_arg, m8_cfa_pw_cl, m8_cfa_pw_col, m8_cfa_pw_esp,
```

```
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width         = TRUE,
    font_size          = 11,
    latex_options      = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 31: Summary fit indices of Stereotype content model: inmmorality

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Men	1043	ML	0 (0)	1	1	0 [0-0]	0	10611.363
	Poor Men	1058	ML	0 (0)	1	1	0 [0-0]	0	10226.111
	Rich Women	1056	ML	0 (0)	1	1	0 [0-0]	0	11025.728
	Poor Women	1052	ML	0 (0)	1	1	0 [0-0]	0	10001.641
Argentina	Rich Men	216	ML	0 (0)	1	1	0 [0-0]	0	2201.534

Table 31: Summary fit indices of Stereotype content model: inmmorality

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Poor Men	219	ML	0 (0)	1	1	0 [0-0]	0	2152.203
	Rich Women	207	ML	0 (0)	1	1	0 [0-0]	0	2180.033
	Poor Women	215	ML	0 (0)	1	1	0 [0-0]	0	2033.150
Chile	Rich Men	217	ML	0 (0)	1	1	0 [0-0]	0	2221.275
	Poor Men	215	ML	0 (0)	1	1	0 [0-0]	0	2058.520
	Rich Women	223	ML	0 (0)	1	1	0 [0-0]	0	2373.823
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	2032.958
Colombia	Rich Men	206	ML	0 (0)	1	1	0 [0-0]	0	2096.875
	Poor Men	214	ML	0 (0)	1	1	0 [0-0]	0	2103.545
	Rich Women	199	ML	0 (0)	1	1	0 [0-0]	0	2052.773
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	2017.228
Spain	Rich Men	195	ML	0 (0)	1	1	0 [0-0]	0	1918.207
	Poor Men	213	ML	0 (0)	1	1	0 [0-0]	0	1919.257
	Rich Women	212	ML	0 (0)	1	1	0 [0-0]	0	2088.505
	Poor Women	211	ML	0 (0)	1	1	0 [0-0]	0	1808.743
México	Rich Men	209	ML	0 (0)	1	1	0 [0-0]	0	2176.784
	Poor Men	197	ML	0 (0)	1	1	0 [0-0]	0	1950.643
	Rich Women	215	ML	0 (0)	1	1	0 [0-0]	0	2302.096

Table 31: Summary fit indices of Stereotype content model: inmmorality

Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Poor Women	216	ML	0 (0)	1	1	0 [0-0]	0	2041.889

5.4.2 Stereotype content model: morality

We included the immorality scale in an exploratory manner. The items are form the published article from Sánchez-Castelló et al. (2022).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("mor_1", "mor_2", "mor_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("mor_1", "mor_2", "mor_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("mor_1", "mor_2", "mor_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("mor_1", "mor_2", "mor_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("mor_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 32: Descriptive statistics of Morality

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	mor_1	1043	3.382	1.357	4	3.389	1.483	1	7	6	0.035	-0.261	0.042
	mor_2	1043	3.555	1.389	4	3.576	1.483	1	7	6	-0.066	-0.181	0.043
	mor_3	1043	3.354	1.367	3	3.349	1.483	1	7	6	0.107	-0.117	0.042
Poor Men	mor_1	1058	4.250	1.367	4	4.244	1.483	1	7	6	0.048	0.084	0.042
	mor_2	1058	4.096	1.389	4	4.087	1.483	1	7	6	0.080	-0.075	0.043
	mor_3	1058	4.082	1.350	4	4.085	1.483	1	7	6	0.026	0.118	0.041
Rich Women	mor_1	1056	3.843	1.402	4	3.852	1.483	1	7	6	-0.070	-0.028	0.043
	mor_2	1056	3.876	1.406	4	3.887	1.483	1	7	6	-0.096	-0.053	0.043
	mor_3	1056	3.728	1.431	4	3.719	1.483	1	7	6	0.031	-0.113	0.044
Poor Women	mor_1	1052	4.667	1.310	4	4.650	1.483	1	7	6	-0.007	-0.210	0.040
	mor_2	1052	4.581	1.377	4	4.571	1.483	1	7	6	-0.011	-0.246	0.042
	mor_3	1052	4.573	1.321	4	4.555	1.483	1	7	6	-0.014	-0.194	0.041

```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rm, c("mor_1", "mor_2", "mor_3")),
      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. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pm, c("mor_1", "mor_2", "mor_3")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rw, c("mor_1", "mor_2", "mor_3")),
      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,
```

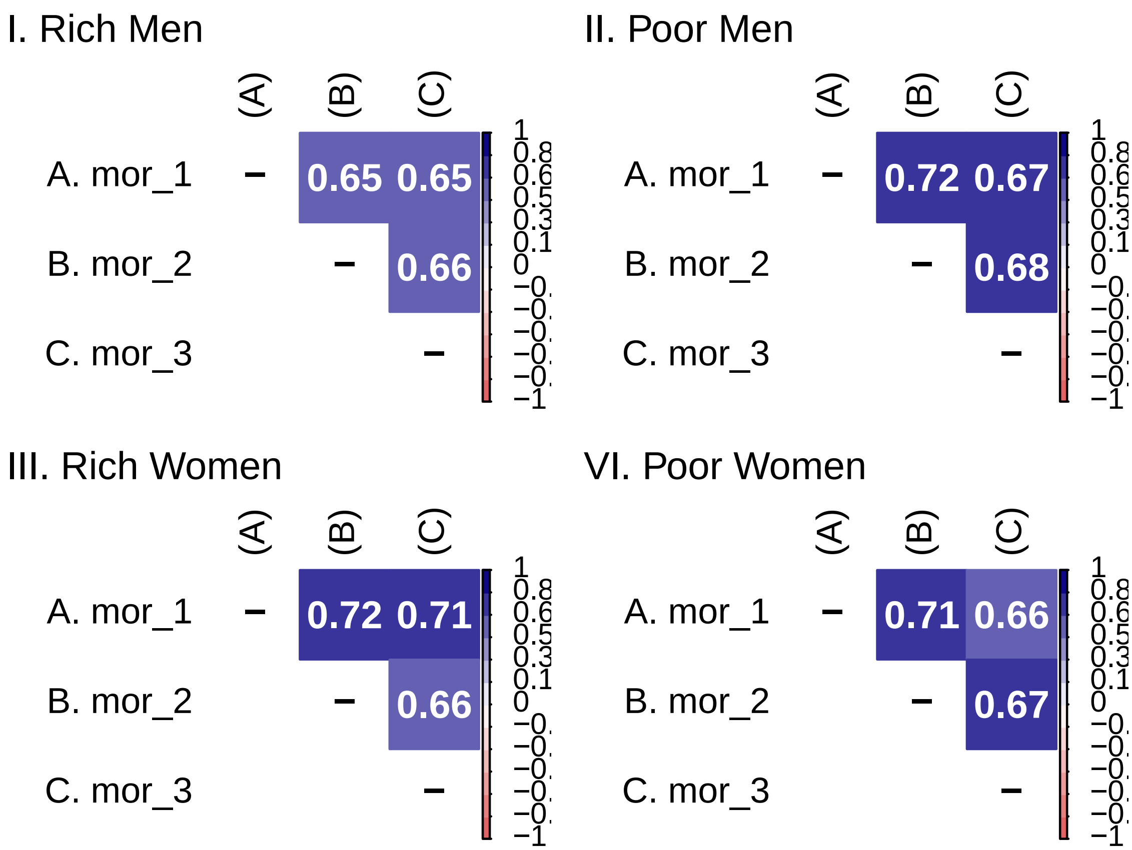
```
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pw, c("mor_1", "mor_2", "mor_3")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
```

```
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 10: Correlation matrix of Morality



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

Reliability

```r
mi_variable <- "mor"
result2 <- alphas(db_proc, c("mor_1", "mor_2", "mor_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8784209
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.333   4.000   4.000   4.667   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("mor_1", "mor_2", "mor_3")], na.rm = TR
```

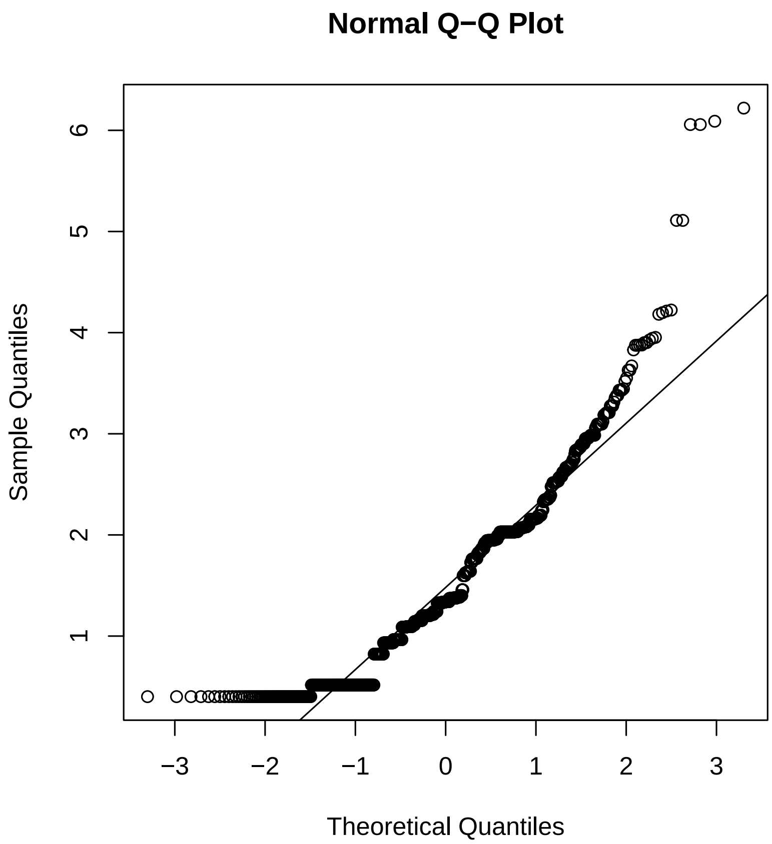
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality for each target.

```r
mardia(db_rm[,c("mor_1", "mor_2", "mor_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("mor_1", "mor_2", "mor_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 0.27 skew = 46.46 with probability <= 0.0000012 small sample skew = 46.66 with probability <= 0.0000011 b2p = 23.23 kurtosis = 24.25

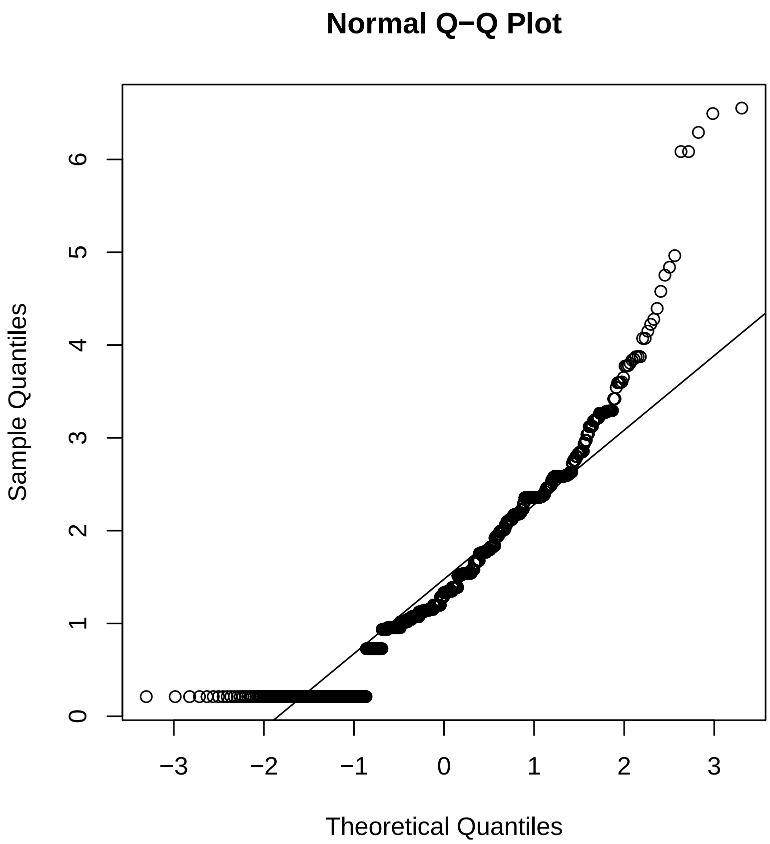


with probability <= 0

```r
mardia(db_pm[,c("mor_1", "mor_2", "mor_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pm[, c("mor_1", "mor_2", "mor_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1058 num.vars = 3 b1p = 0.72 skew = 127.47 with probability <= 0.000000000000000000000015 small sample skew = 128.01 with probability <= 0.000000000000000000000012 b2p = 26.15 kurtosis = 33.1 with probability <=

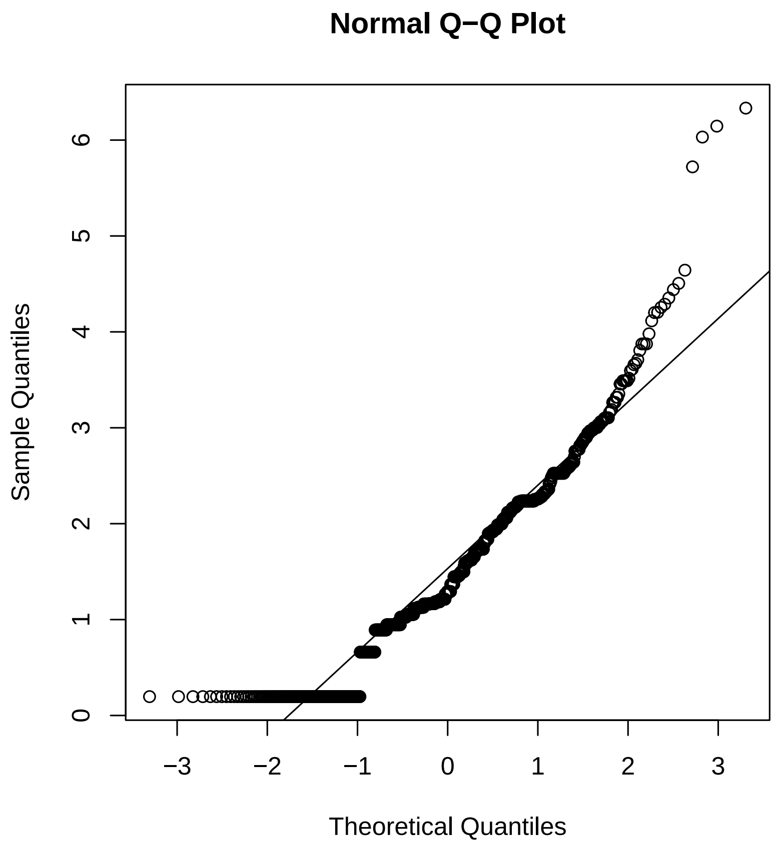


0

```
mardia(db_rw[,c("mor_1", "mor_2", "mor_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rw[, c("mor_1", "mor_2", "mor_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1056 num.vars = 3 b1p = 0.06 skew = 11.1 with probability <= 0.35 small sample skew = 11.15 with probability <= 0.35 b2p = 23.08 kurtosis = 23.96 with

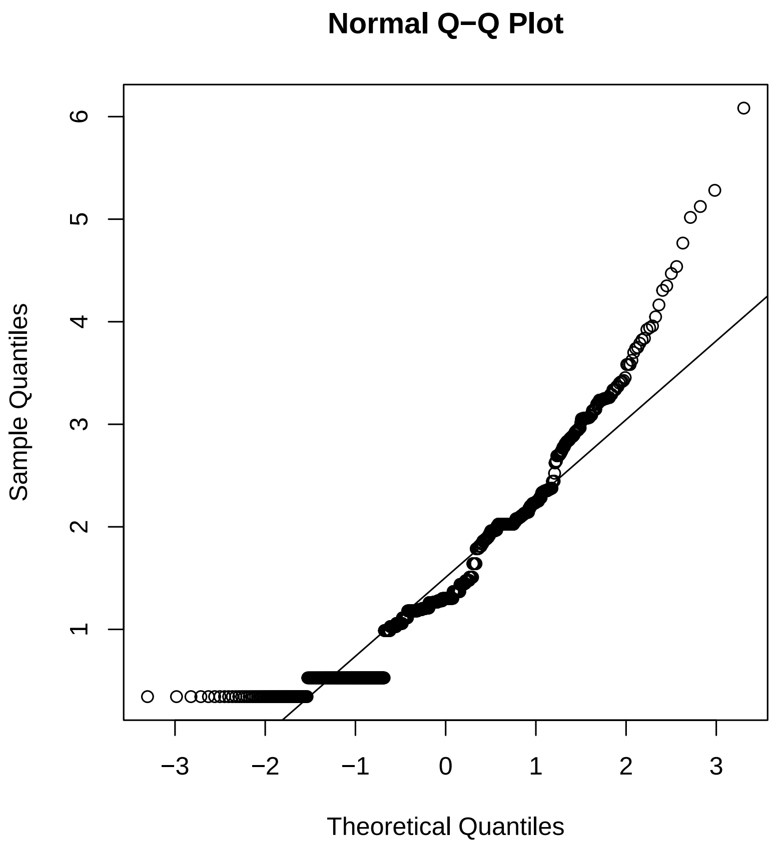


probability <= 0

```
mardia(db_pw[,c("mor_1", "mor_2", "mor_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pw[, c("mor_1", "mor_2", "mor_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1052 num.vars = 3 b1p = 0.18 skew = 31.33 with probability <= 0.00052 small sample skew = 31.46 with probability <= 0.00049 b2p = 21.73 kurtosis = 19.93



with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  morality =~ mor_1 + mor_2 + mor_3
   '

# estimation
# overall
m9_cfa_rm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

```
m9_cfa_pm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m9_cfa_rw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m9_cfa_pw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)


# argentina
m9_cfa_rm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m9_cfa_pm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m9_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m9_cfa_pw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Women"),
```

```
                  estimator = "MLR",
                  ordered = F,
                  std.lv = F)

# chile
m9_cfa_rm_cl <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "3.Rich.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m9_cfa_pm_cl <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "3.Poor.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m9_cfa_rw_cl <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "3.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m9_cfa_pw_cl <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "3.Poor.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

# colombia
m9_cfa_rm_col <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "4.Rich.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m9_cfa_pm_col <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "4.Poor.Men"),
                      estimator = "MLR",
                      ordered = F,
```

```
                     std.lv = F)

m9_cfa_rw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m9_cfa_pw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# españa
m9_cfa_rm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m9_cfa_pm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m9_cfa_rw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m9_cfa_pw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# mexico
```

```r
m9_cfa_rm_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m9_cfa_pm_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m9_cfa_rw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m9_cfa_pw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```r
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m9_cfa_rm, m9_cfa_rm_arg, m9_cfa_rm_cl, m9_cfa_rm_col, m9_cfa_rm_esp,
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Men")
,
cfa_tab_fit(
  models = list(m9_cfa_pm, m9_cfa_pm_arg, m9_cfa_pm_cl, m9_cfa_pm_col, m9_cfa_pm_esp,
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Men")
,
```

```
cfa_tab_fit(
  models = list(m9_cfa_rw, m9_cfa_rw_arg, m9_cfa_rw_cl, m9_cfa_rw_col, m9_cfa_rw_esp,
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
,
cfa_tab_fit(
  models = list(m9_cfa_pw, m9_cfa_pw_arg, m9_cfa_pw_cl, m9_cfa_pw_col, m9_cfa_pw_esp,
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 33: Summary fit indices of Stereotype content model: morality

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Men	1043	ML	0 (0)	1	1	0 [0-0]	0	9540.692

Table 33: Summary fit indices of Stereotype content model: morality

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Poor Men	1058	ML	0 (0)	1	1	0 [0-0]	0	9440.719
	Rich Women	1056	ML	0 (0)	1	1	0 [0-0]	0	9566.324
	Poor Women	1052	ML	0 (0)	1	1	0 [0-0]	0	9294.452
Argentina	Rich Men	216	ML	0 (0)	1	1	0 [0-0]	0	2052.651
	Poor Men	219	ML	0 (0)	1	1	0 [0-0]	0	1947.442
	Rich Women	207	ML	0 (0)	1	1	0 [0-0]	0	1818.548
	Poor Women	215	ML	0 (0)	1	1	0 [0-0]	0	1884.272
Chile	Rich Men	217	ML	0 (0)	1	1	0 [0-0]	0	1946.342
	Poor Men	215	ML	0 (0)	1	1	0 [0-0]	0	1912.601
	Rich Women	223	ML	0 (0)	1	1	0 [0-0]	0	2071.733
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	1794.739
Colombia	Rich Men	206	ML	0 (0)	1	1	0 [0-0]	0	1929.650
	Poor Men	214	ML	0 (0)	1	1	0 [0-0]	0	2049.164
	Rich Women	199	ML	0 (0)	1	1	0 [0-0]	0	1817.104
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	1901.407
Spain	Rich Men	195	ML	0 (0)	1	1	0 [0-0]	0	1533.123
	Poor Men	213	ML	0 (0)	1	1	0 [0-0]	0	1615.871
	Rich Women	212	ML	0 (0)	1	1	0 [0-0]	0	1680.451

Table 33: Summary fit indices of Stereotype content model: morality

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Poor Women	211	ML	0 (0)	1	1	0 [0-0]	0	1751.336
México	Rich Men	209	ML	0 (0)	1	1	0 [0-0]	0	2003.526
	Poor Men	197	ML	0 (0)	1	1	0 [0-0]	0	1817.122
	Rich Women	215	ML	0 (0)	1	1	0 [0-0]	0	2083.032
	Poor Women	216	ML	0 (0)	1	1	0 [0-0]	0	1919.010

5.4.3 Stereotype content model: warmth

We included the immorality scale in an exploratory manner. The items are form the published article from Sánchez-Castelló et al. (2022).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("war_1", "war_2", "war_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("war_1", "war_2", "war_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("war_1", "war_2", "war_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("war_1", "war_2", "war_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
```

```r
) %>%
  mutate(vars = paste0("war_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 34: Descriptive statistics of Warmth

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	war_1	1043	3.889	1.416	4	3.890	1.483	1	7	6	-0.014	-0.130	0.044
	war_2	1043	3.557	1.329	4	3.575	1.483	1	7	6	-0.054	-0.182	0.041
	war_3	1043	3.954	1.318	4	3.982	1.483	1	7	6	-0.217	0.086	0.041
Poor Men	war_1	1058	4.398	1.303	4	4.399	1.483	1	7	6	-0.082	0.172	0.040
	war_2	1058	4.060	1.309	4	4.068	1.483	1	7	6	-0.008	0.286	0.040
	war_3	1058	4.314	1.311	4	4.314	1.483	1	7	6	-0.011	0.127	0.040
Rich Women	war_1	1056	3.941	1.434	4	3.962	1.483	1	7	6	-0.151	-0.164	0.044
	war_2	1056	3.758	1.394	4	3.749	1.483	1	7	6	0.009	-0.046	0.043
	war_3	1056	4.088	1.390	4	4.118	1.483	1	7	6	-0.155	-0.010	0.043
Poor Women	war_1	1052	4.799	1.288	5	4.811	1.483	1	7	6	-0.114	-0.059	0.040
	war_2	1052	4.608	1.293	4	4.603	1.483	1	7	6	-0.088	0.087	0.040
	war_3	1052	4.761	1.236	5	4.751	1.483	1	7	6	0.009	-0.021	0.038

```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rm, c("war_1", "war_2", "war_3")),
      method = "color",
```

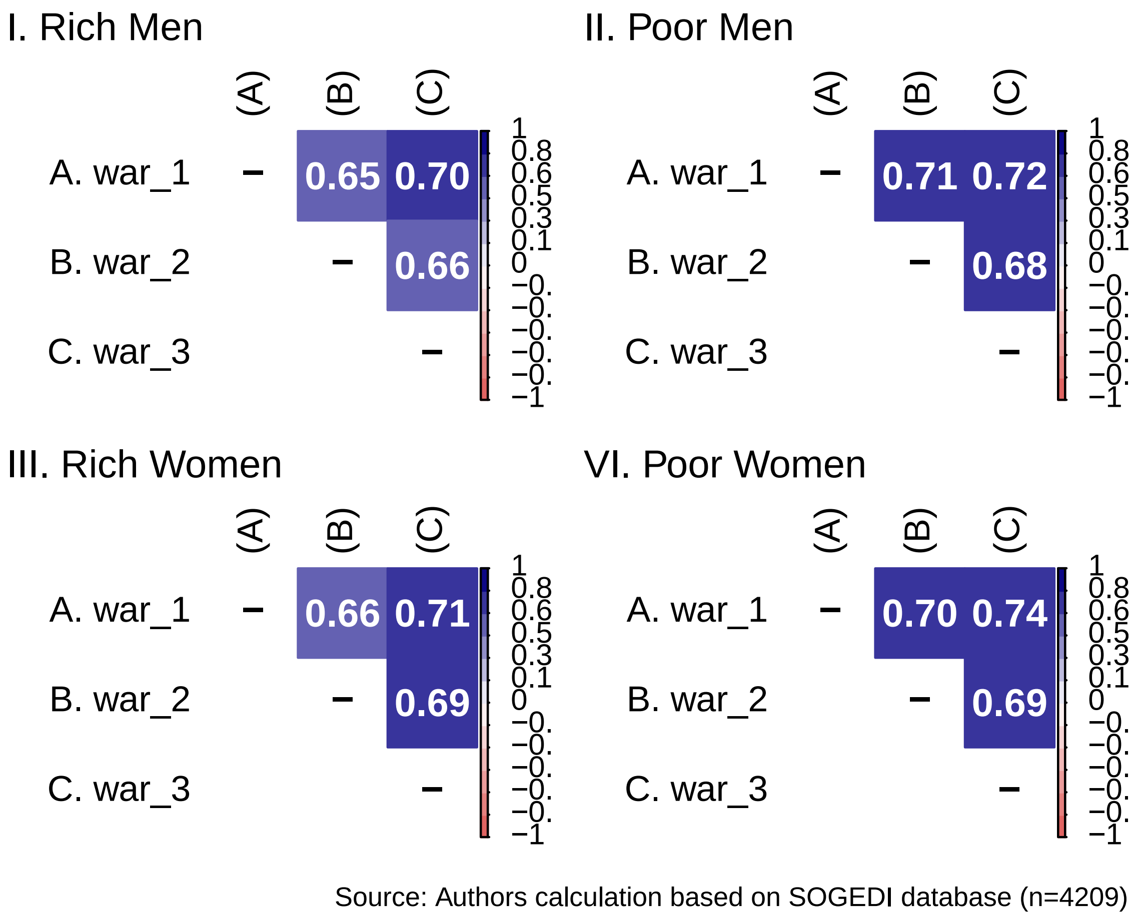
```
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      rect.col = "black",
      addCoef.col = "white",
      cl.cex = 0.8,
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pm, c("war_1", "war_2", "war_3")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rw, c("war_1", "war_2", "war_3")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pw, c("war_1", "war_2", "war_3")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
```

```r
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 11: Correlation matrix of Warmth



Reliability

```
mi_variable <- "war"
result2 <- alphas(db_proc, c("war_1", "war_2", "war_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8808715
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.333   4.000   4.178   5.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("war_1", "war_2", "war_3")], na.rm = TR
```

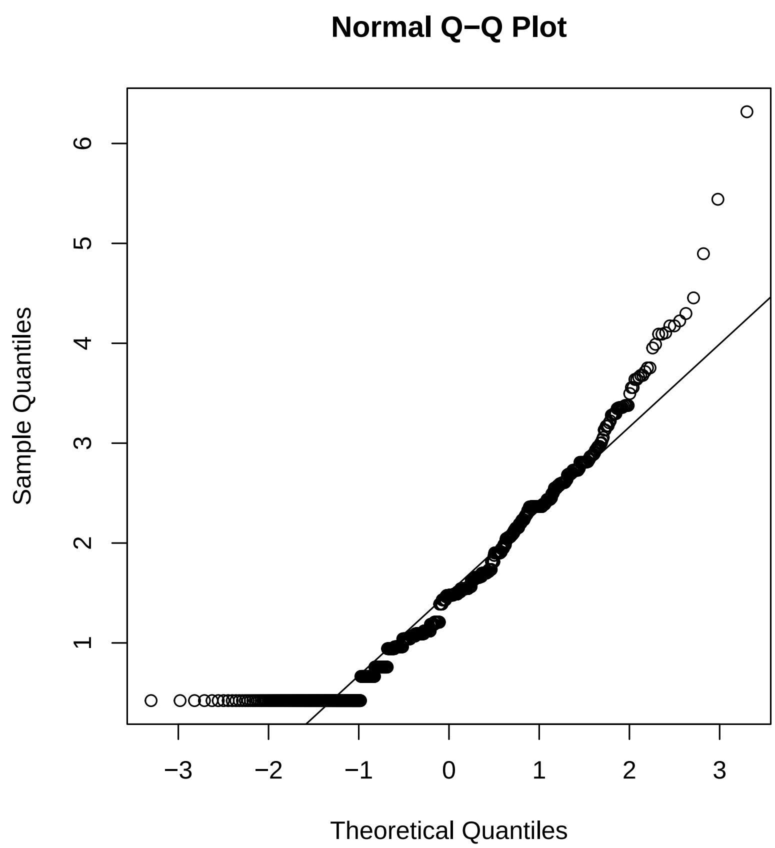
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality for each target.

```
mardia(db_rm[,c("war_1", "war_2", "war_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("war_1", "war_2", "war_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 0.34 skew = 59.18 with probability <= 0.0000000052 small sample skew = 59.43 with probability <= 0.0000000046 b2p = 20.73 kurtosis =

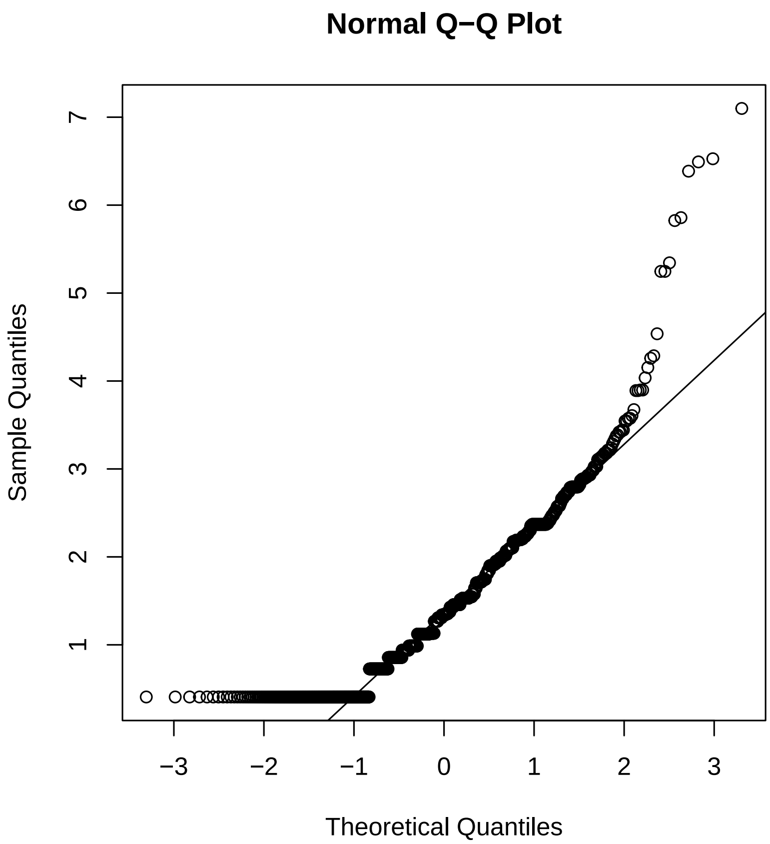


16.9 with probability <= 0

```r
mardia(db_pm[,c("war_1", "war_2", "war_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pm[, c("war_1", "war_2", "war_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1058 num.vars = 3 b1p = 0.51 skew = 89.74 with probability <= 0.000000000000006 small sample skew = 90.12 with probability <= 0.0000000000000051 b2p = 27.61 kurtosis = 37.43 with probability <=

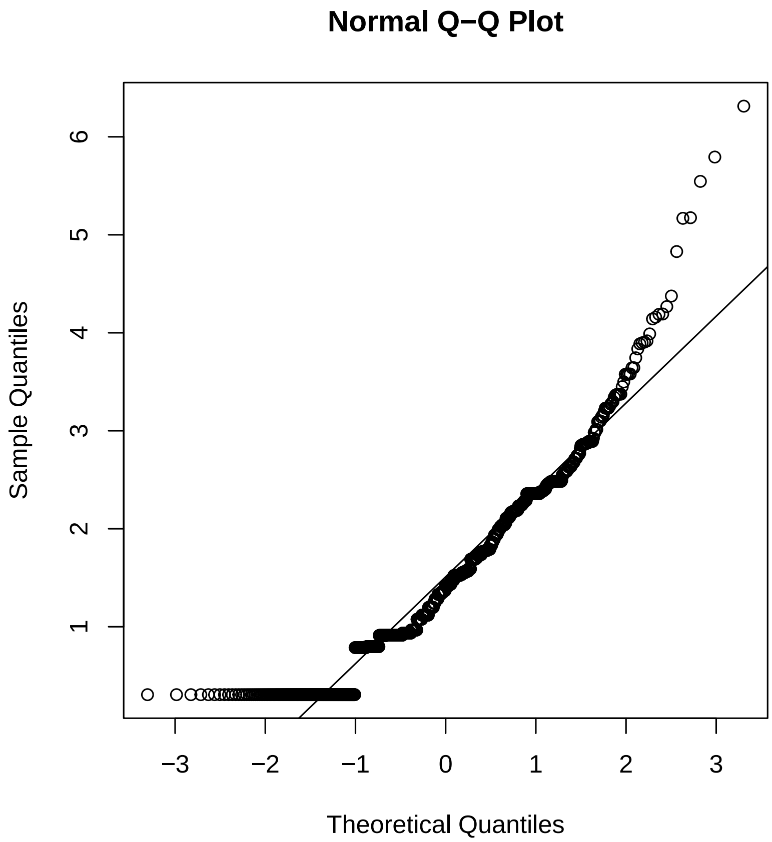


0

```r
mardia(db_rw[,c("war_1", "war_2", "war_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rw[, c("war_1", "war_2", "war_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1056 num.vars = 3 b1p = 0.25 skew = 44.72 with probability <= 0.0000024 small sample skew = 44.91 with probability <= 0.0000023 b2p = 22.3 kurtosis = 21.67

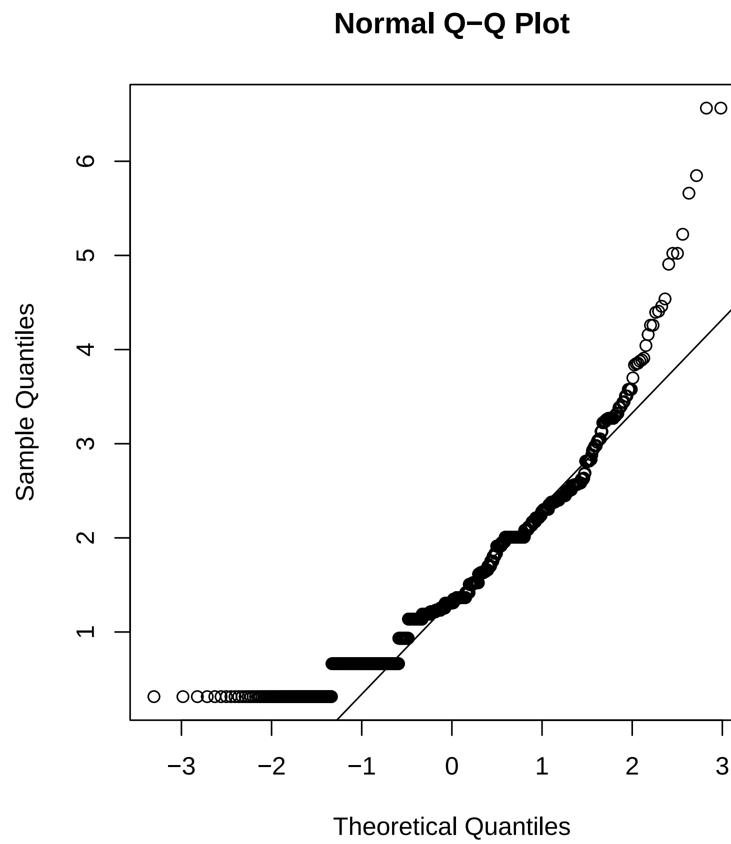


with probability <= 0

```
mardia(db_pw[,c("war_1", "war_2", "war_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pw[, c("war_1", "war_2", "war_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1052 num.vars = 3 b1p = 1.6 skew = 279.82 with probability <= 0.000000000000000000000000000000000000000000000000028 small sample skew = 281.02 with probability <= 0.000000000000000000000000000000000000000000000000016



b2p = 26.18 kurtosis = 33.09 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  warmth =~ war_1 + war_2 + war_3
   '

# estimation
# overall
m10_cfa_rm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

```
m10_cfa_pm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m10_cfa_rw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m10_cfa_pw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)


# argentina
m10_cfa_rm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m10_cfa_pm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m10_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m10_cfa_pw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Women"),
```

```
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile
m10_cfa_rm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_pm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_pw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia
m10_cfa_rm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_pm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
```

```
                     std.lv = F)

m10_cfa_rw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_pw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# españa
m10_cfa_rm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_pm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_rw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m10_cfa_pw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# mexico
```

```r
m10_cfa_rm_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Rich.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m10_cfa_pm_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Poor.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m10_cfa_rw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m10_cfa_pw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Poor.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)
```

```r
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m10_cfa_rm, m10_cfa_rm_arg, m10_cfa_rm_cl, m10_cfa_rm_col, m10_cfa_rm_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Men")
,
cfa_tab_fit(
  models = list(m10_cfa_pm, m10_cfa_pm_arg, m10_cfa_pm_cl, m10_cfa_pm_col, m10_cfa_pm_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Men")
,
```

```r
cfa_tab_fit(
  models = list(m10_cfa_rw, m10_cfa_rw_arg, m10_cfa_rw_cl, m10_cfa_rw_col, m10_cfa_rw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
,
cfa_tab_fit(
  models = list(m10_cfa_pw, m10_cfa_pw_arg, m10_cfa_pw_cl, m10_cfa_pw_col, m10_cfa_pw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 35: Summary fit indices of Stereotype content model: Warmth

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Men	1043	ML	0 (0)	1	1	0 [0-0]	0	9332.975

Table 35: Summary fit indices of Stereotype content model: Warmth

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Poor Men	1058	ML	0 (0)	1	1	0 [0-0]	0	9057.274
	Rich Women	1056	ML	0 (0)	1	1	0 [0-0]	0	9612.983
	Poor Women	1052	ML	0 (0)	1	1	0 [0-0]	0	8793.574
Argentina	Rich Men	216	ML	0 (0)	1	1	0 [0-0]	0	1934.807
	Poor Men	219	ML	0 (0)	1	1	0 [0-0]	0	1911.227
	Rich Women	207	ML	0 (0)	1	1	0 [0-0]	0	1837.963
	Poor Women	215	ML	0 (0)	1	1	0 [0-0]	0	1740.027
Chile	Rich Men	217	ML	0 (0)	1	1	0 [0-0]	0	1990.219
	Poor Men	215	ML	0 (0)	1	1	0 [0-0]	0	1893.533
	Rich Women	223	ML	0 (0)	1	1	0 [0-0]	0	2044.606
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	1781.331
Colombia	Rich Men	206	ML	0 (0)	1	1	0 [0-0]	0	1841.377
	Poor Men	214	ML	0 (0)	1	1	0 [0-0]	0	1820.878
	Rich Women	199	ML	0 (0)	1	1	0 [0-0]	0	1866.105
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	1798.193
Spain	Rich Men	195	ML	0 (0)	1	1	0 [0-0]	0	1604.356
	Poor Men	213	ML	0 (0)	1	1	0 [0-0]	0	1558.266
	Rich Women	212	ML	0 (0)	1	1	0 [0-0]	0	1722.409

Table 35: Summary fit indices of Stereotype content model: Warmth

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Poor Women	211	ML	0 (0)	1	1	0 [0-0]	0	1619.085
México	Rich Men	209	ML	0 (0)	1	1	0 [0-0]	0	1931.478
	Poor Men	197	ML	0 (0)	1	1	0 [0-0]	0	1784.471
	Rich Women	215	ML	0 (0)	1	1	0 [0-0]	0	2069.670
	Poor Women	216	ML	0 (0)	1	1	0 [0-0]	0	1773.125

5.4.4 Stereotype content model: competence

We included the immorality scale in an exploratory manner. The items are form the published article from Sánchez-Castelló et al. (2022).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("com_1", "com_2", "com_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("com_1", "com_2", "com_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("com_1", "com_2", "com_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("com_1", "com_2", "com_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
```

```
) %>%
  mutate(vars = paste0("co_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 36: Descriptive statistics of Competence

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	co_1	1043	5.017	1.396	5	5.104	1.483	1	7	6	-0.500	0.084	0.043
	co_2	1043	5.058	1.458	5	5.175	1.483	1	7	6	-0.615	0.046	0.045
	co_3	1043	4.825	1.418	5	4.879	1.483	1	7	6	-0.393	-0.149	0.044
Poor Men	co_1	1058	4.262	1.393	4	4.268	1.483	1	7	6	0.007	-0.126	0.043
	co_2	1058	4.573	1.418	4	4.590	1.483	1	7	6	-0.178	-0.133	0.044
	co_3	1058	4.232	1.420	4	4.231	1.483	1	7	6	0.033	-0.112	0.044
Rich Women	co_1	1056	4.863	1.420	5	4.937	1.483	1	7	6	-0.482	0.034	0.044
	co_2	1056	4.808	1.469	5	4.891	1.483	1	7	6	-0.496	-0.042	0.045
	co_3	1056	4.680	1.514	5	4.764	1.483	1	7	6	-0.476	-0.068	0.047
Poor Women	co_1	1052	4.643	1.437	4	4.648	1.483	1	7	6	-0.011	-0.523	0.044
	co_2	1052	4.900	1.399	5	4.943	1.483	1	7	6	-0.181	-0.418	0.043
	co_3	1052	4.630	1.430	4	4.643	1.483	1	7	6	-0.085	-0.301	0.044

```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rm, c("com_1", "com_2", "com_3")),
      method = "color",
```

```r
      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. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pm, c("com_1", "com_2", "com_3")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rw, c("com_1", "com_2", "com_3")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_pw, c("com_1", "com_2", "com_3")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
```

```
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

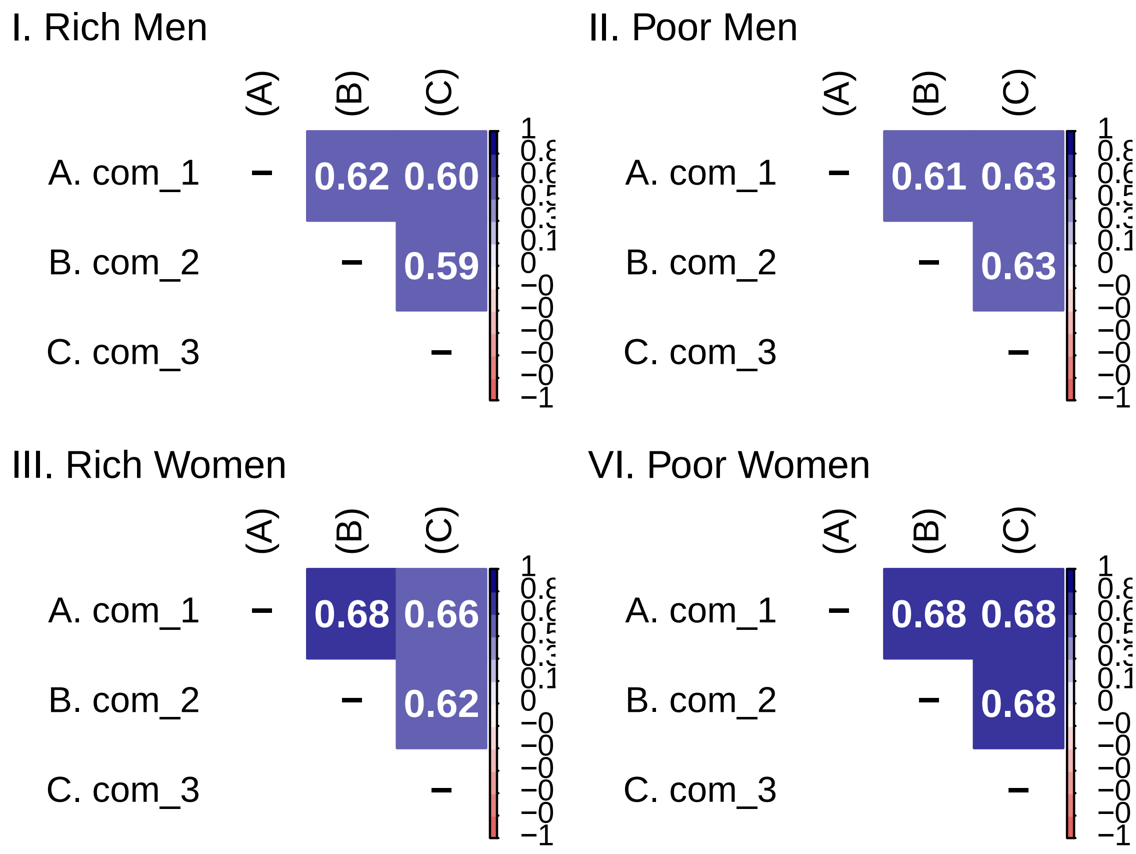
```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 12: Correlation matrix of Competence



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

Reliability

```
mi_variable <- "com"
result2 <- alphas(db_proc, c("com_1", "com_2", "com_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8456987
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   4.000   4.667   4.707   5.667   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("com_1", "com_2", "com_3")], na.rm = TR
```

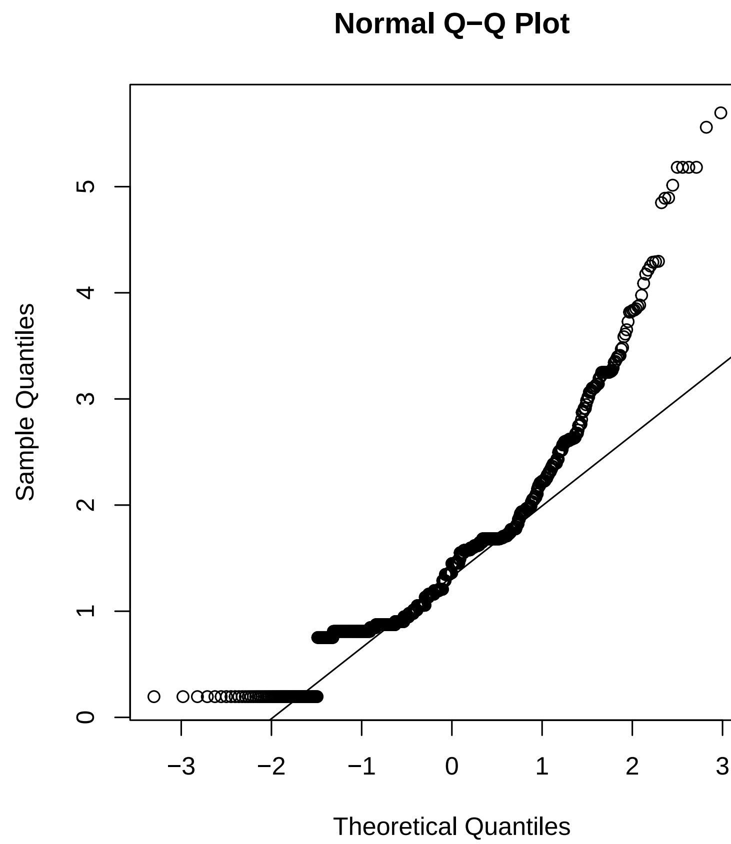
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality for each target.

```
mardia(db_rm[,c("com_1", "com_2", "com_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("com_1", "com_2", "com_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 1.53 skew = 265.7 with probability <= 0.000000000000000000000000000000000000000000000000027 small sample skew = 266.85 with probability <= 0.000000000000000000000000000000000000000000000000015

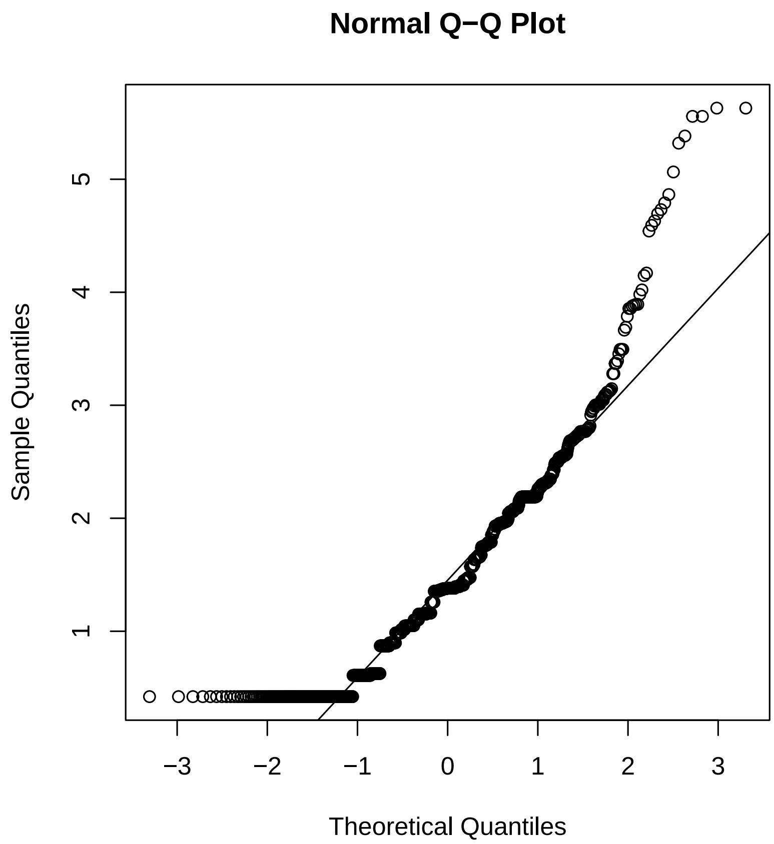


b2p = 24.08 kurtosis = 26.77 with probability <= 0

```
mardia(db_pm[,c("com_1", "com_2", "com_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pm[, c("com_1", "com_2", "com_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1058 num.vars = 3 b1p = 1.14 skew = 200.6 with probability <= 0.000000000000000000000000000000000000012 small sample skew = 201.46 with probability <= 0.000000000000000000000000000000000000008 b2p = 23.72 kurtosis = 25.89

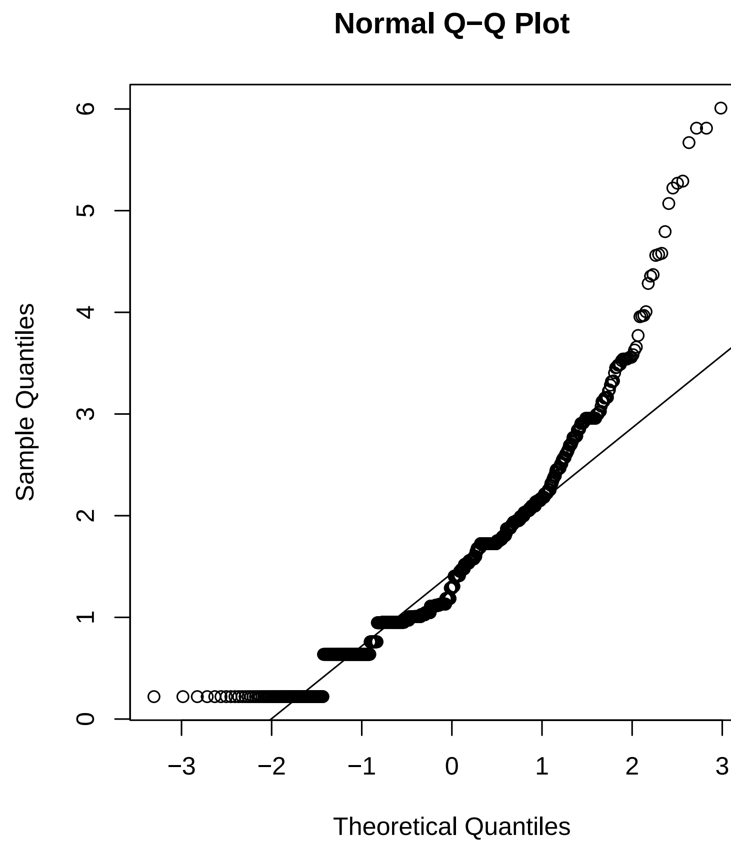


with probability <= 0

```
mardia(db_rw[,c("com_1", "com_2", "com_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rw[, c("com_1", "com_2", "com_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1056 num.vars = 3 b1p = 1.64 skew = 288.46 with probability <= 0.000000000000000000000000000000000000000000000000000043 small sample skew = 289.69 with probability <= 0.000000000000000000000000000000000000000000000000000023

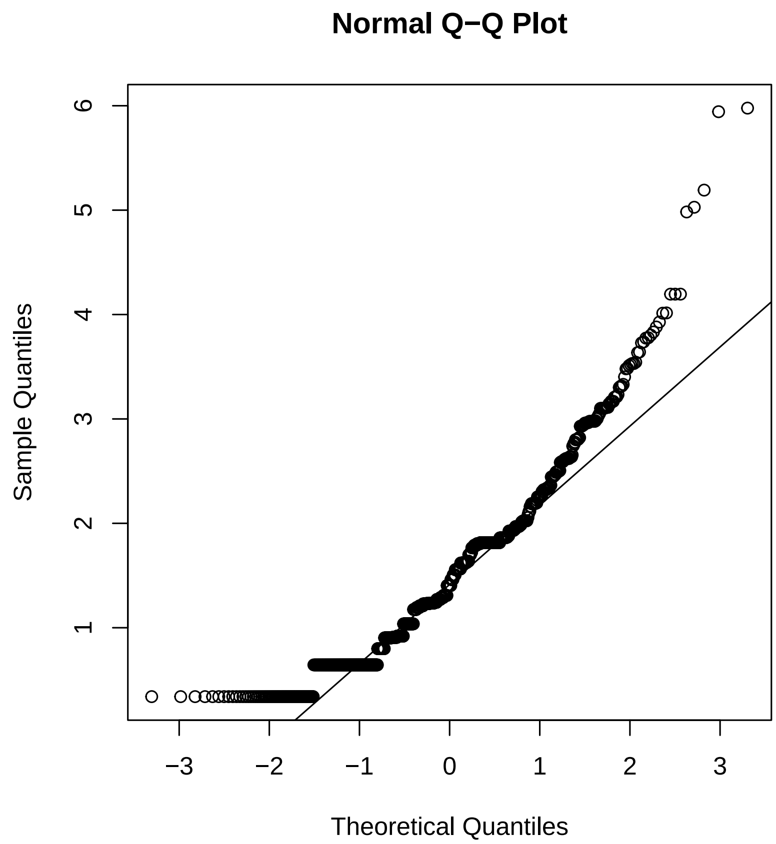


b2p = 25.42 kurtosis = 30.91 with probability <= 0

```
mardia(db_pw[,c("com_1", "com_2", "com_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pw[, c("com_1", "com_2", "com_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1052 num.vars = 3 b1p = 0.99 skew = 173.94 with probability <= 0.000000000000000000000000000000042 small sample skew = 174.68 with probability <= 0.00000000000000000000000000000003 b2p = 20.86 kurtosis = 17.36 with probabil-



ity <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  competence =~ com_1 + com_2 + com_3
   '

# estimation
# overall
m11_cfa_rm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

```r
m11_cfa_pm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m11_cfa_rw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m11_cfa_pw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)


# argentina
m11_cfa_rm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m11_cfa_pm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m11_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m11_cfa_pw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Women"),
```

```
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile
m11_cfa_rm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m11_cfa_pm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m11_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m11_cfa_pw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia
m11_cfa_rm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m11_cfa_pm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
```

```
                      std.lv = F)

m11_cfa_rw_col <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "4.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m11_cfa_pw_col <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "4.Poor.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

# españa
m11_cfa_rm_esp <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "9.Rich.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m11_cfa_pm_esp <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "9.Poor.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m11_cfa_rw_esp <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "9.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m11_cfa_pw_esp <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "9.Poor.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

# mexico
```

```
m11_cfa_rm_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Rich.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m11_cfa_pm_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Poor.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m11_cfa_rw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)

m11_cfa_pw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Poor.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)
```

```
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m11_cfa_rm, m11_cfa_rm_arg, m11_cfa_rm_cl, m11_cfa_rm_col, m11_cfa_rm_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Men")
,
cfa_tab_fit(
  models = list(m11_cfa_pm, m11_cfa_pm_arg, m11_cfa_pm_cl, m11_cfa_pm_col, m11_cfa_pm_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Men")
,
```

```
cfa_tab_fit(
  models = list(m11_cfa_rw, m11_cfa_rw_arg, m11_cfa_rw_cl, m11_cfa_rw_col, m11_cfa_rw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
,
cfa_tab_fit(
  models = list(m11_cfa_pw, m11_cfa_pw_arg, m11_cfa_pw_cl, m11_cfa_pw_col, m11_cfa_pw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 37: Summary fit indices of Stereotype content model: competence

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Men	1043	ML	0 (0)	1	1	0 [0-0]	0	9988.796

Table 37: Summary fit indices of Stereotype content model: competence

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Poor Men	1058	ML	0 (0)	1	1	0 [0-0]	0	9988.798
	Rich Women	1056	ML	0 (0)	1	1	0 [0-0]	0	10070.509
	Poor Women	1052	ML	0 (0)	1	1	0 [0-0]	0	9690.783
Argentina	Rich Men	216	ML	0 (0)	1	1	0 [0-0]	0	2142.351
	Poor Men	219	ML	0 (0)	1	1	0 [0-0]	0	2107.183
	Rich Women	207	ML	0 (0)	1	1	0 [0-0]	0	1987.870
	Poor Women	215	ML	0 (0)	1	1	0 [0-0]	0	2005.088
Chile	Rich Men	217	ML	0 (0)	1	1	0 [0-0]	0	2097.180
	Poor Men	215	ML	0 (0)	1	1	0 [0-0]	0	2047.067
	Rich Women	223	ML	0 (0)	1	1	0 [0-0]	0	2188.017
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	1843.429
Colombia	Rich Men	206	ML	0 (0)	1	1	0 [0-0]	0	1893.569
	Poor Men	214	ML	0 (0)	1	1	0 [0-0]	0	2024.499
	Rich Women	199	ML	0 (0)	1	1	0 [0-0]	0	1803.823
	Poor Women	205	ML	0 (0)	1	1	0 [0-0]	0	1967.218
Spain	Rich Men	195	ML	0 (0)	1	1	0 [0-0]	0	1698.793
	Poor Men	213	ML	0 (0)	1	1	0 [0-0]	0	1798.758
	Rich Women	212	ML	0 (0)	1	1	0 [0-0]	0	1831.850

Table 37: Summary fit indices of Stereotype content model: competence

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Poor Women	211	ML	0 (0)	1	1	0 [0-0]	0	1767.824
México	Rich Men	209	ML	0 (0)	1	1	0 [0-0]	0	2077.541
	Poor Men	197	ML	0 (0)	1	1	0 [0-0]	0	1907.408
	Rich Women	215	ML	0 (0)	1	1	0 [0-0]	0	2199.605
	Poor Women	216	ML	0 (0)	1	1	0 [0-0]	0	2024.340

5.4.5 Intergroup behavioural tendencies: passive harm

This behavior scale is a combination of two scales by López-Rodríguez et al. (2017) and López-Rodríguez et al. (2016), modified to better fit our context. We utilized the scale from the second paper and made adjustments to some collaboration items to better align it with our objectives and the groups being assessed.

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("ph_1", "ph_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("ph_1", "ph_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("ph_1", "ph_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("ph_1", "ph_2")]) %>%
```

```r
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("ph_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 38: Descriptive statistics of Intergroup behavioural tendencies: passive harm

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	ph_1	1043	2.424	1.637	2	2.169	1.483	1	7	6	1.033	0.245	0.051
	ph_2	1043	2.802	1.800	2	2.574	1.483	1	7	6	0.683	-0.535	0.056
Poor Men	ph_1	1058	2.309	1.600	2	2.053	1.483	1	7	6	1.063	0.195	0.049
	ph_2	1058	2.332	1.537	2	2.106	1.483	1	7	6	0.978	0.152	0.047
Rich Women	ph_1	1056	2.302	1.645	2	2.019	1.483	1	7	6	1.166	0.485	0.051
	ph_2	1056	2.460	1.657	2	2.219	1.483	1	7	6	0.921	-0.092	0.051
Poor Women	ph_1	1052	1.754	1.297	1	1.468	0.000	1	7	6	1.852	2.908	0.040
	ph_2	1052	1.833	1.278	1	1.587	0.000	1	7	6	1.522	1.600	0.039

```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("ph_1", "ph_2")),
      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,
```

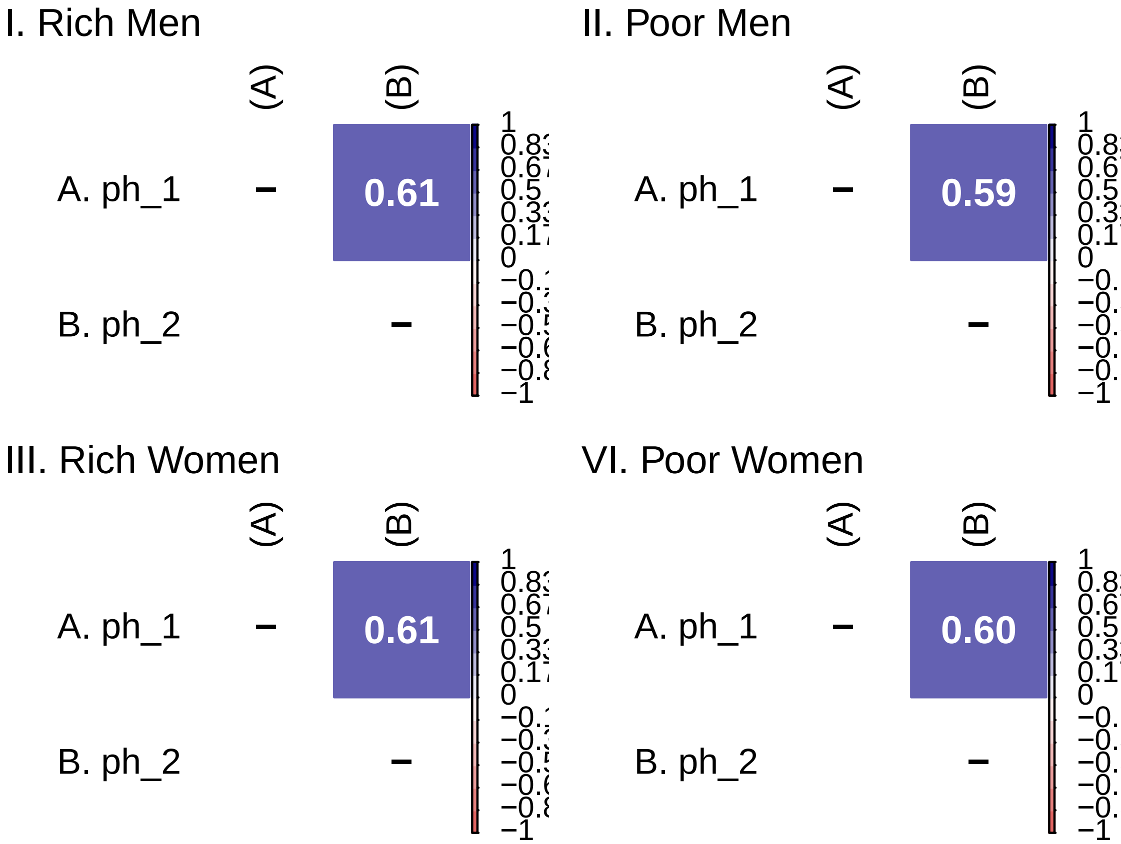
```r
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("ph_1", "ph_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("ph_1", "ph_2")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("ph_1", "ph_2")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 13: Correlation matrix of Intergroup behavioural tendencies: passive harm



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

Reliability

```r
mi_variable <- "ph"
result2 <- alphas(db_proc, c("ph_1", "ph_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7595042
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.000   2.000   2.276   3.500   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("ph_1", "ph_2")], na.rm = TRUE)
```

5.4.6 Intergroup behavioural tendencies: active harm

This behavior scale is a combination of two scales by Lucía Lopez, modified to better fit our context. We utilized the scale from the second paper and made adjustments to some collaboration items to better align it with our objectives and the groups being assessed.

Descriptive analysis

```r
bind_rows(
psych::describe(db_rm[,c("ah_1", "ah_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("ah_1", "ah_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("ah_1", "ah_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
```

```r
psych::describe(db_pw[,c("ah_1", "ah_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("ah_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 39: Descriptive statistics of Intergroup behavioural tendencies: active harm

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	ah_1	1043	2.366	1.605	2	2.104	1.483	1	7	6	1.088	0.425	0.050
	ah_2	1043	2.256	1.600	2	1.969	1.483	1	7	6	1.232	0.702	0.050
Poor Men	ah_1	1058	1.725	1.277	1	1.435	0.000	1	7	6	1.965	3.430	0.039
	ah_2	1058	1.579	1.169	1	1.277	0.000	1	7	6	2.339	5.361	0.036
Rich Women	ah_1	1056	2.119	1.480	1	1.868	0.000	1	7	6	1.272	0.901	0.046
	ah_2	1056	2.054	1.469	1	1.784	0.000	1	7	6	1.309	0.770	0.045
Poor Women	ah_1	1052	1.509	1.097	1	1.220	0.000	1	7	6	2.568	6.859	0.034
	ah_2	1052	1.432	1.003	1	1.147	0.000	1	6	5	2.520	5.675	0.031

```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("ah_1", "ah_2")),
      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',
```

```r
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("ah_1", "ah_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("ah_1", "ah_2")),
      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,
```

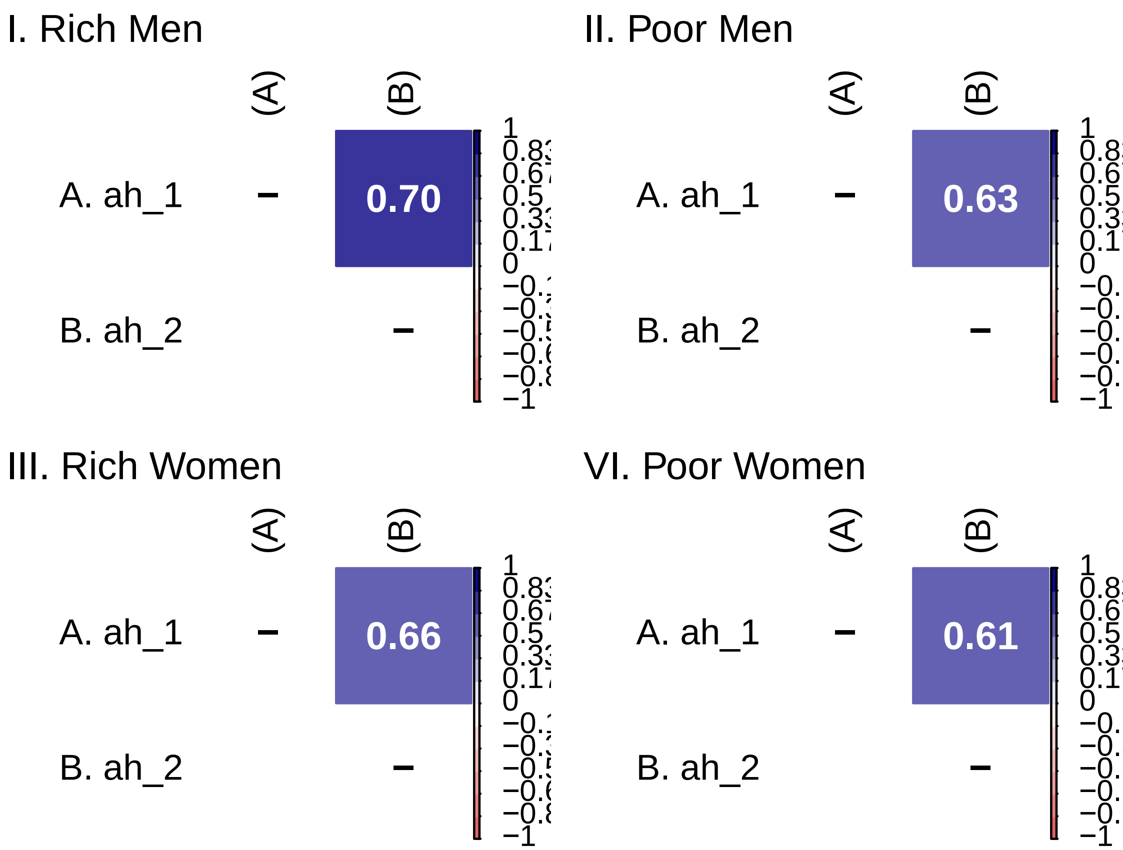
```r
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("ah_1", "ah_2")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
```

```
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 14: Correlation matrix of Intergroup behavioural tendencies: active harm



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

Reliability

```r
mi_variable <- "ah"
result2 <- alphas(db_proc, c("ah_1", "ah_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8090044
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.000   1.000   1.879   2.500   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("ah_1", "ah_2")], na.rm = TRUE)
```

5.4.7 Intergroup behavioural tendencies: passive facilitation

This behavior scale is a combination of two scales by Lucía Lopez, modified to better fit our context. We utilized the scale from the second paper and made adjustments to some collaboration items to better align it with our objectives and the groups being assessed.

Descriptive analysis

```r
bind_rows(
psych::describe(db_rm[,c("pf_1", "pf_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("pf_1", "pf_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("pf_1", "pf_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
```

```r
psych::describe(db_pw[,c("pf_1", "pf_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("pf_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 40: Descriptive statistics of Intergroup behavioural tendencies: passive facilitation

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	pf_1	1043	4.421	1.579	4	4.484	1.483	1	7	6	-0.248	-0.245	0.049
	pf_2	1043	4.417	1.775	4	4.515	1.483	1	7	6	-0.322	-0.672	0.055
Poor Men	pf_1	1058	5.112	1.653	5	5.298	1.483	1	7	6	-0.713	-0.120	0.051
	pf_2	1058	3.604	1.737	4	3.534	1.483	1	7	6	0.204	-0.694	0.053
Rich Women	pf_1	1056	4.375	1.686	4	4.435	1.483	1	7	6	-0.216	-0.568	0.052
	pf_2	1056	4.577	1.766	5	4.694	1.483	1	7	6	-0.369	-0.632	0.054
Poor Women	pf_1	1052	5.462	1.552	6	5.673	1.483	1	7	6	-0.914	0.337	0.048
	pf_2	1052	4.185	1.741	4	4.214	1.483	1	7	6	-0.072	-0.743	0.054

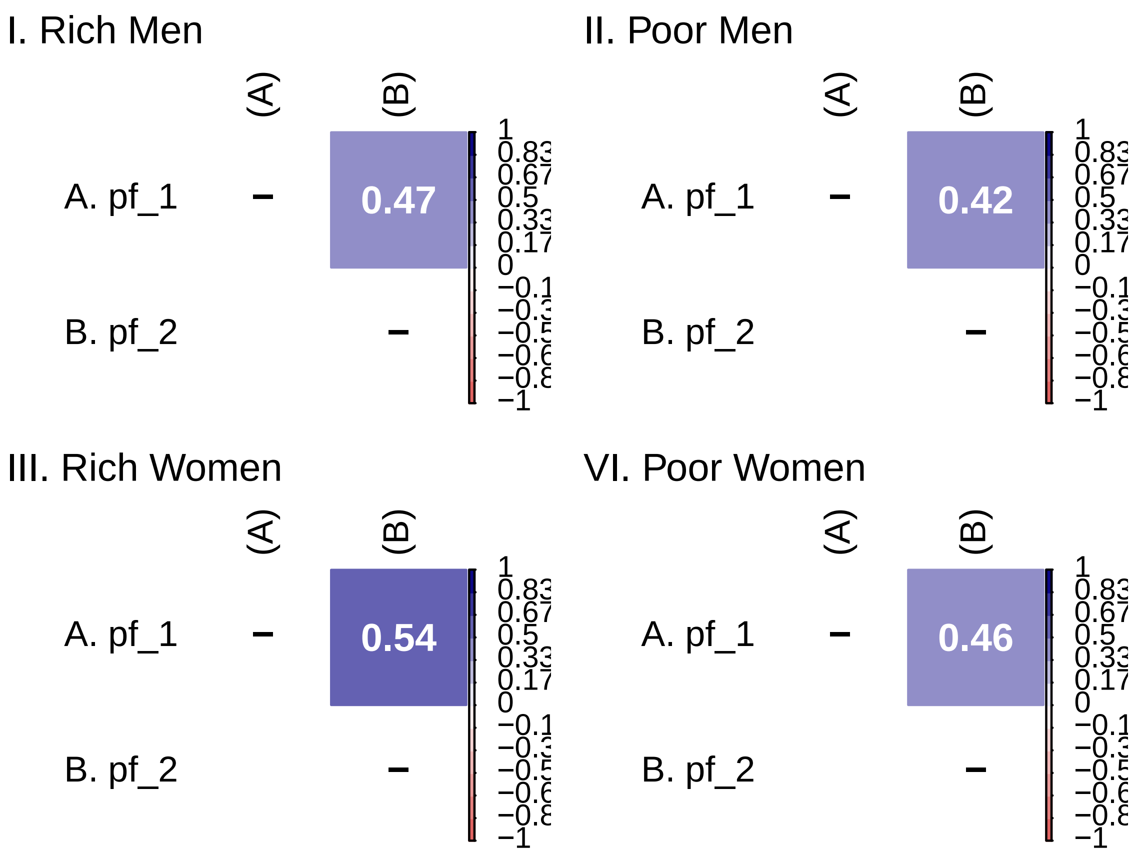
```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("pf_1", "pf_2")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
```

```r
      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. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("pf_1", "pf_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("pf_1", "pf_2")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("pf_1", "pf_2")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 15: Correlation matrix of Intergroup behavioural tendencies: passive facilitation



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

Reliability

```
mi_variable <- "pf"
result2 <- alphas(db_proc, c("pf_1", "pf_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.5800451
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.500   4.500   4.519   5.500   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("pf_1", "pf_2")], na.rm = TRUE)
```

5.4.8 Intergroup behavioural tendencies: active facilitation

This behavior scale is a combination of two scales by Lucía Lopez, modified to better fit our context. We utilized the scale from the second paper and made adjustments to some collaboration items to better align it with our objectives and the groups being assessed.

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("af_1", "af_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("af_1", "af_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("af_1", "af_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
```

```
,
psych::describe(db_pw[,c("af_1", "af_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("af_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 41: Descriptive statistics of Intergroup behavioural tendencies: active facilitation

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	af_1	1043	3.967	1.744	4	3.964	1.483	1	7	6	-0.069	-0.718	0.054
	af_2	1043	3.975	1.710	4	3.974	1.483	1	7	6	-0.075	-0.618	0.053
Poor Men	af_1	1058	3.899	1.747	4	3.876	1.483	1	7	6	0.075	-0.813	0.054
	af_2	1058	4.541	1.632	4	4.614	1.483	1	7	6	-0.201	-0.512	0.050
Rich Women	af_1	1056	4.177	1.752	4	4.209	1.483	1	7	6	-0.089	-0.771	0.054
	af_2	1056	4.200	1.754	4	4.248	1.483	1	7	6	-0.143	-0.710	0.054
Poor Women	af_1	1052	4.391	1.714	4	4.441	1.483	1	7	6	-0.115	-0.731	0.053
	af_2	1052	4.935	1.558	5	5.043	1.483	1	7	6	-0.382	-0.424	0.048

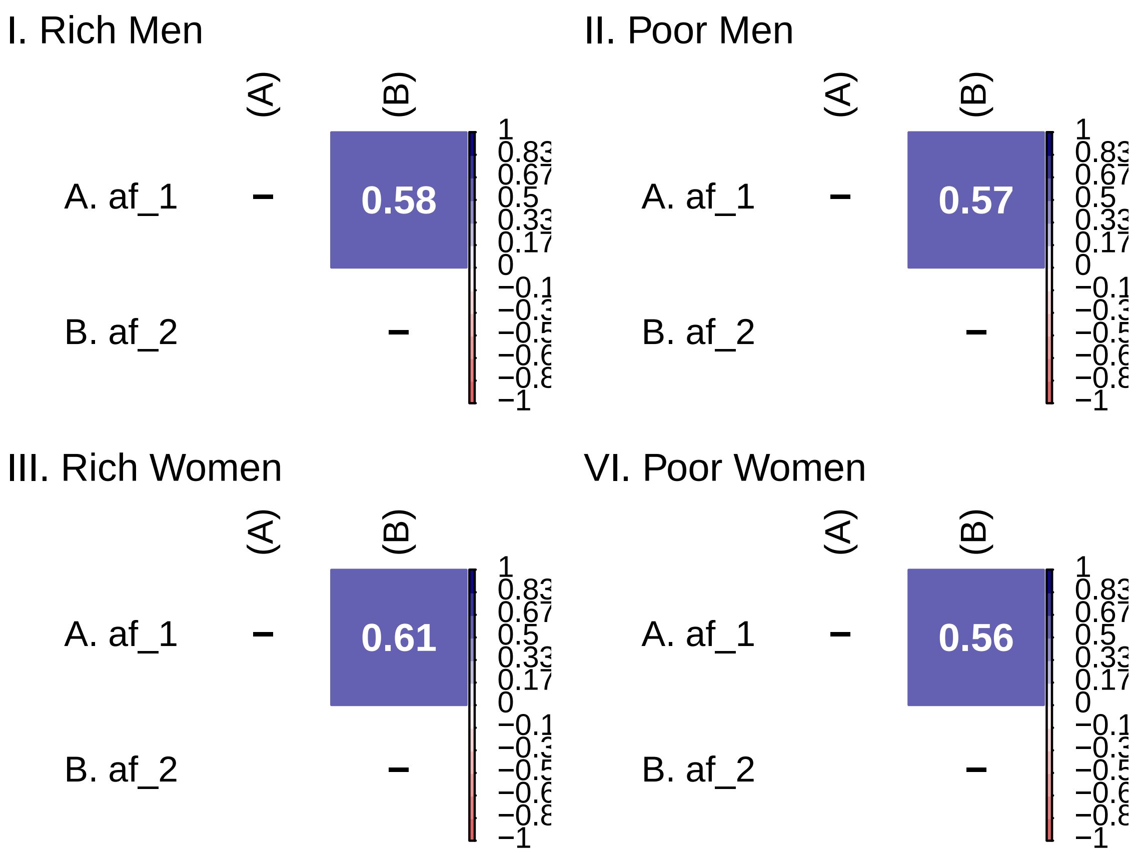
```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("af_1", "af_2")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
```

```r
      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. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("af_1", "af_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("af_1", "af_2")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("af_1", "af_2")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 16: Correlation matrix of Intergroup behavioural tendencies: active facilitation



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

Reliability

```
mi_variable <- "af"
result2 <- alphas(db_proc, c("af_1", "af_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7310643
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.000   4.000   4.261   5.500   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("af_1", "af_2")], na.rm = TRUE)
```

5.4.9 Intergroup affect tendencies: admiration toward

We selected emotions that have been used in various studies that test the BIAS map from Cuddy et al. (2007).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("ad_1", "ad_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("ad_1", "ad_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("ad_1", "ad_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("ad_1", "ad_2")]) %>%
```

```
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("ad_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 42: Descriptive statistics of Intergroup affect tendencies: admiration toward

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	ad_1	1043	4.046	1.812	4	4.057	1.483	1	7	6	-0.139	-0.847	0.056
	ad_2	1043	4.290	1.724	4	4.351	1.483	1	7	6	-0.213	-0.638	0.053
Poor Men	ad_1	1058	3.552	1.789	4	3.473	1.483	1	7	6	0.145	-0.804	0.055
	ad_2	1058	5.155	1.674	5	5.330	1.483	1	7	6	-0.618	-0.396	0.051
Rich Women	ad_1	1056	4.036	1.911	4	4.045	2.965	1	7	6	-0.134	-1.024	0.059
	ad_2	1056	4.619	1.747	5	4.745	1.483	1	7	6	-0.401	-0.562	0.054
Poor Women	ad_1	1052	4.288	1.821	4	4.360	1.483	1	7	6	-0.249	-0.745	0.056
	ad_2	1052	5.636	1.475	6	5.831	1.483	1	7	6	-0.989	0.514	0.045

```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("ad_1", "ad_2")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      rect.col = "black",
```

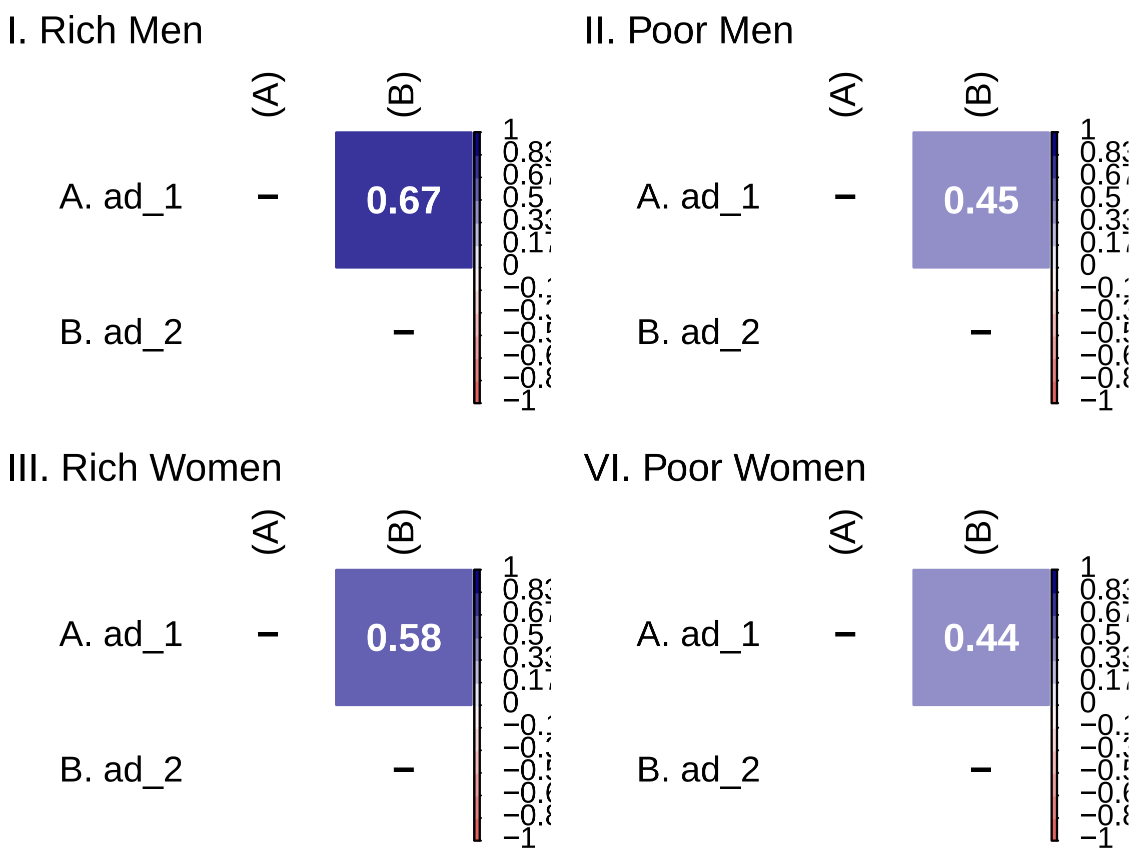
```r
      addCoef.col = "white",
      cl.cex = 0.8,
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("ad_1", "ad_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("ad_1", "ad_2")),
      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",
```

```r
      cl.cex = 0.8,
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("ad_1", "ad_2")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
```

```
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 17: Correlation matrix of Intergroup affect tendencies: admiration toward



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

Reliability

```
mi_variable <- "ad"
result2 <- alphas(db_proc, c("ad_1", "ad_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.67663
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.500   4.500   4.453   5.500   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("ad_1", "ad_2")], na.rm = TRUE)
```

5.4.10 Intergroup affect tendencies: contempt toward

We selected emotions that have been used in various studies that test the BIAS map from Cuddy et al. (2007).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("co_1", "co_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("co_1", "co_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("co_1", "co_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("co_1", "co_2")]) %>%
```

```
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("co_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 43: Descriptive statistics of Intergroup affect tendencies: contempt toward

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	co_1	1043	2.062	1.500	1	1.790	0	1	7	6	1.341	0.903	0.046
	co_2	1043	2.228	1.567	1	1.968	0	1	7	6	1.099	0.251	0.049
Poor Men	co_1	1058	1.722	1.229	1	1.456	0	1	7	6	1.805	2.708	0.038
	co_2	1058	1.617	1.155	1	1.335	0	1	7	6	2.103	4.187	0.036
Rich Women	co_1	1056	1.770	1.333	1	1.481	0	1	7	6	1.790	2.481	0.041
	co_2	1056	1.886	1.381	1	1.618	0	1	7	6	1.556	1.638	0.043
Poor Women	co_1	1052	1.390	0.935	1	1.128	0	1	7	6	2.843	8.460	0.029
	co_2	1052	1.343	0.842	1	1.113	0	1	7	6	2.935	9.447	0.026

```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("co_1", "co_2")),
      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,
```

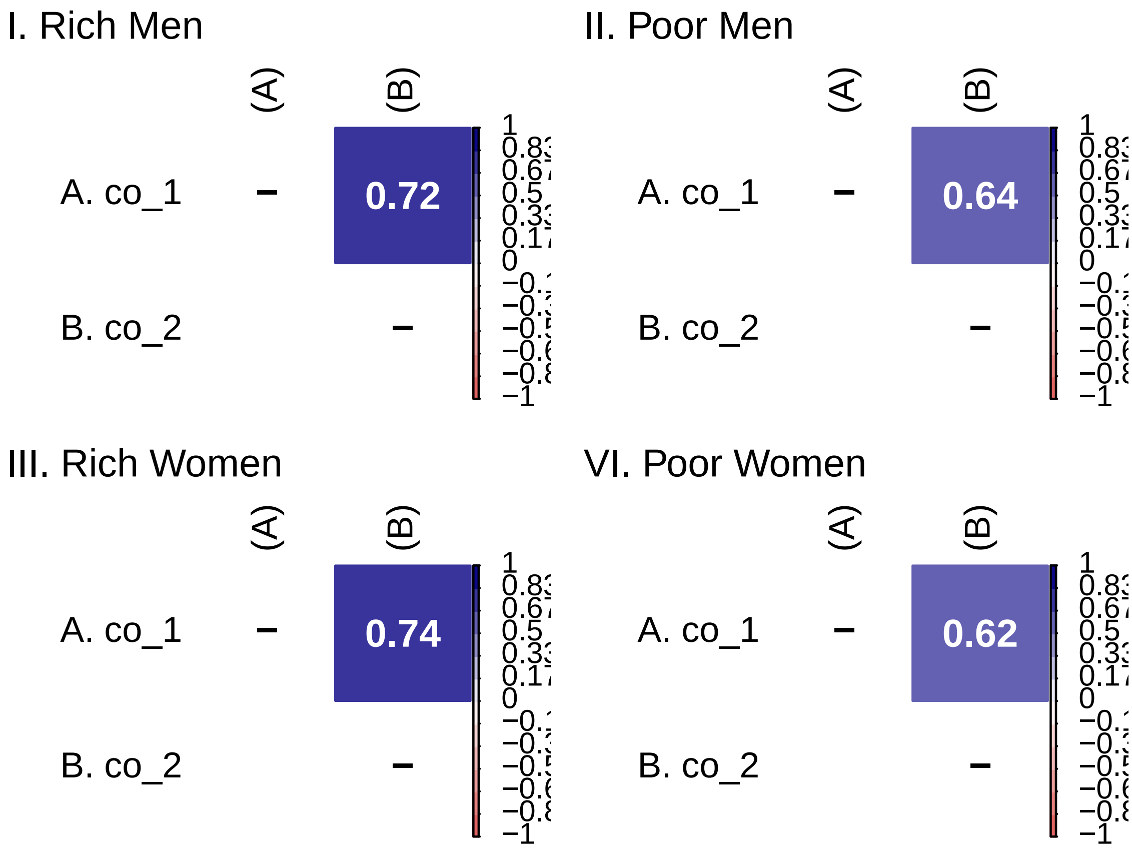
```r
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("co_1", "co_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("co_1", "co_2")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("co_1", "co_2")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 18: Correlation matrix of Intergroup affect tendencies: contempt toward



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

Reliability

```
mi_variable <- "co"
result2 <- alphas(db_proc, c("co_1", "co_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8274669
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.000   1.000   1.751   2.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("co_1", "co_2")], na.rm = TRUE)
```

5.4.11 Intergroup affect tendencies: envy toward

We selected emotions that have been used in various studies that test the BIAS map from Cuddy et al. (2007).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("en_1", "en_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("en_1", "en_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("en_1", "en_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("en_1", "en_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("en_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 44: Descriptive statistics of Intergroup affect tendencies: envy toward

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	en_1	1043	2.338	1.611	2	2.090	1.483	1	7	6	1.000	0.034	0.050
	en_2	1043	2.205	1.545	1	1.944	0.000	1	7	6	1.124	0.315	0.048
Poor Men	en_1	1058	1.509	1.050	1	1.232	0.000	1	7	6	2.323	5.264	0.032
	en_2	1058	1.491	1.036	1	1.217	0.000	1	7	6	2.354	5.404	0.032
Rich Women	en_1	1056	2.192	1.560	1	1.922	0.000	1	7	6	1.171	0.379	0.048
	en_2	1056	2.089	1.499	1	1.820	0.000	1	7	6	1.264	0.677	0.046
Poor Women	en_1	1052	1.355	0.920	1	1.102	0.000	1	7	6	3.218	11.559	0.028
	en_2	1052	1.375	0.975	1	1.101	0.000	1	7	6	3.126	10.292	0.030

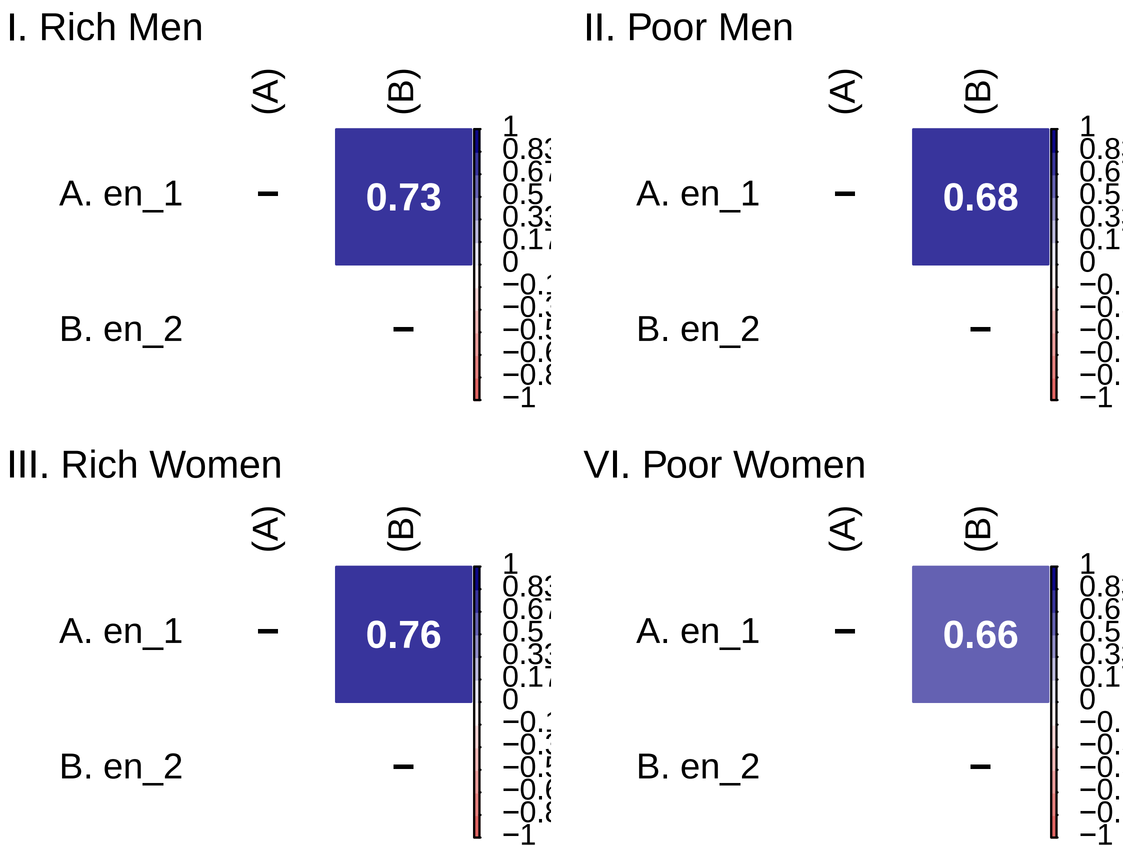
```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("en_1", "en_2")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      rect.col = "black",
      addCoef.col = "white",
      cl.cex = 0.8,
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("en_1", "en_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("en_1", "en_2")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("en_1", "en_2")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
```

```r
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 19: Correlation matrix of Intergroup affect tendencies: envy toward



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

Reliability

```
mi_variable <- "en"
result2 <- alphas(db_proc, c("en_1", "en_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8530262
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.000   1.000   1.818   2.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("en_1", "en_2")], na.rm = TRUE)
```

5.4.12 Intergroup affect tendencies: pity toward

We selected emotions that have been used in various studies that test the BIAS map from Cuddy et al. (2007).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("pi_1", "pi_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_pm[,c("pi_1", "pi_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_rw[,c("pi_1", "pi_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
,
psych::describe(db_pw[,c("pi_1", "pi_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = paste0("pi_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 45: Descriptive statistics of Intergroup affect tendencies: pity toward

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	pi_1	1043	2.062	1.449	1	1.814	0.000	1	7	6	1.265	0.734	0.045
	pi_2	1043	2.213	1.459	2	2.019	1.483	1	7	6	0.961	0.022	0.045
Poor Men	pi_1	1058	3.336	1.895	3	3.226	2.965	1	7	6	0.202	-1.111	0.058
	pi_2	1058	4.006	1.826	4	4.007	1.483	1	7	6	-0.162	-0.855	0.056
Rich Women	pi_1	1056	1.959	1.435	1	1.696	0.000	1	7	6	1.451	1.309	0.044
	pi_2	1056	2.261	1.540	2	2.026	1.483	1	7	6	1.049	0.238	0.047
Poor Women	pi_1	1052	3.199	1.910	3	3.053	2.965	1	7	6	0.320	-1.081	0.059
	pi_2	1052	4.108	1.880	4	4.135	1.483	1	7	6	-0.176	-0.943	0.058

```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("pi_1", "pi_2")),
      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. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
```

```r
      fit_correlations_pairwise(db_pm, c("pi_1", "pi_2")),
      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. Poor Men")

p3 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("pi_1", "pi_2")),
      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 = "III. Rich Women")

p4 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("pi_1", "pi_2")),
      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 = "VI. Poor Women")

a <- p1 + p2

b <- p3 + p4

a/b +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=", nrow(db_proc), ")"
      )
    )
```

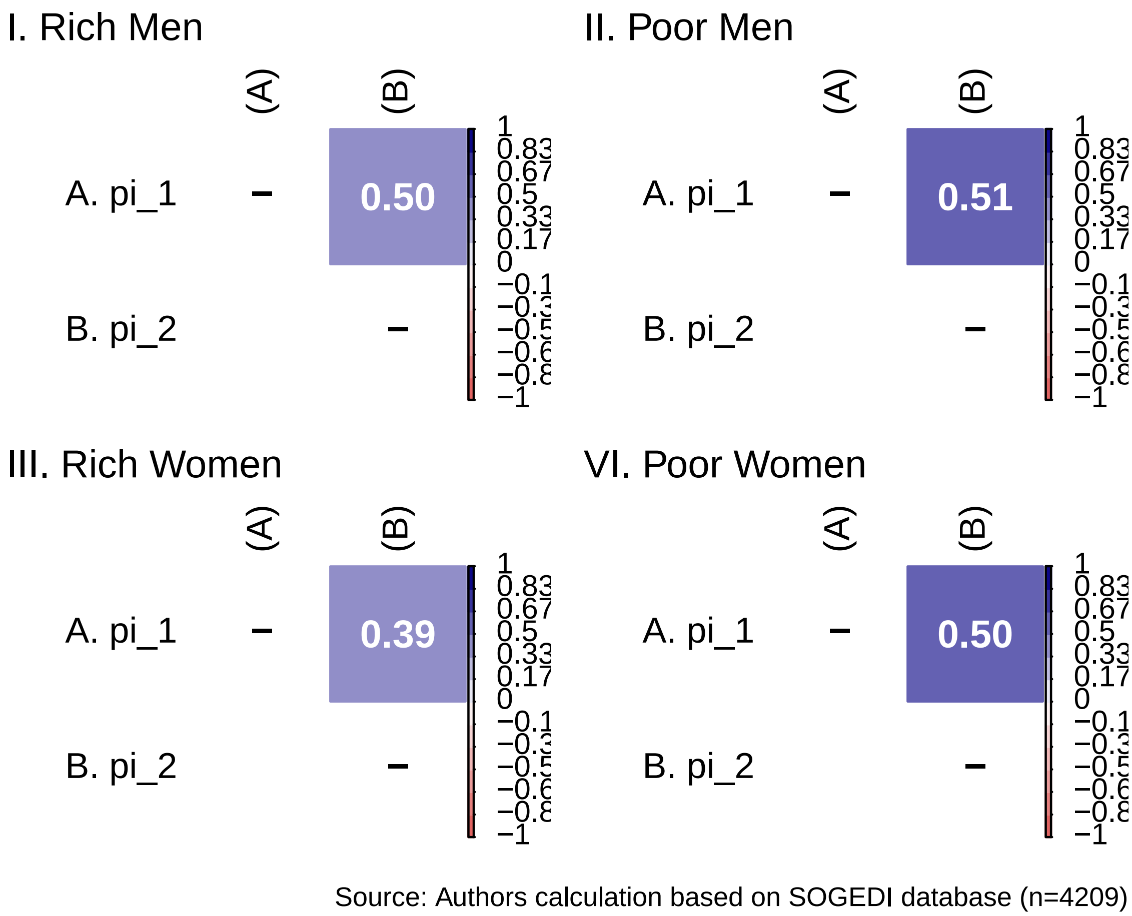
```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 20: Correlation matrix of Intergroup affect tendencies: pity toward



Reliability

```
mi_variable <- "pi"
result2 <- alphas(db_proc, c("pi_1", "pi_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7178623
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.000   2.500   2.895   4.000   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("pi_1", "pi_2")], na.rm = TRUE)
```

5.4.13 Greedy dispositions

X

Descriptive analysis

```r
bind_rows(
psych::describe(db_rm[,c("greedy_1", "greedy_2", "greedy_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_rw[,c("greedy_1", "greedy_2", "greedy_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
) %>%
  mutate(vars = paste0("greedy_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 46: Descriptive statistics of Greedy dispositions

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	greedy_1	1043	5.354	1.716	6	5.604	1.483	1	7	6	-0.920	0.073	0.053
	greedy_2	1043	5.021	1.644	5	5.177	1.483	1	7	6	-0.602	-0.292	0.051
	greedy_3	1043	5.057	1.630	5	5.208	1.483	1	7	6	-0.555	-0.350	0.050
Rich Women	greedy_1	1056	4.644	1.831	5	4.793	1.483	1	7	6	-0.403	-0.675	0.056

Table 46: Descriptive statistics of Greedy dispositions

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
	greedy_2	1056	4.445	1.733	4	4.525	1.483	1	7	6	-0.266	-0.657	0.053
	greedy_3	1056	4.929	1.603	5	5.052	1.483	1	7	6	-0.405	-0.401	0.049

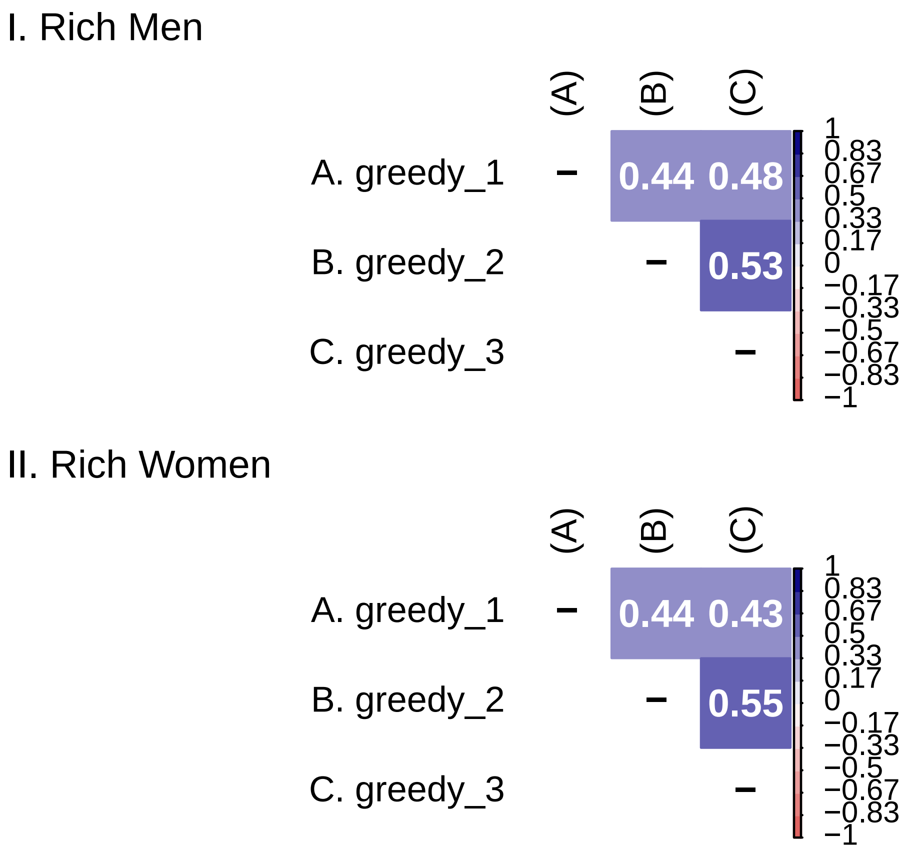
```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rm, c("greedy_1", "greedy_2", "greedy_3")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      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. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rw, c("greedy_1", "greedy_2", "greedy_3")),
      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,
```

```r
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "II. Rich Women")





p1/p2 +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=1043)"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 21: Correlation matrix of Greedy dispositions



Source: Authors calculation based on SOGEDI database (n=1043)

Reliability

```r
mi_variable <- "greedy"
result2 <- alphas(db_proc, c("greedy_1", "greedy_2", "greedy_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7350066
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   4.000   5.000   4.907   6.000   7.000    2110 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("greedy_1", "greedy_2", "greedy_3")], n
```

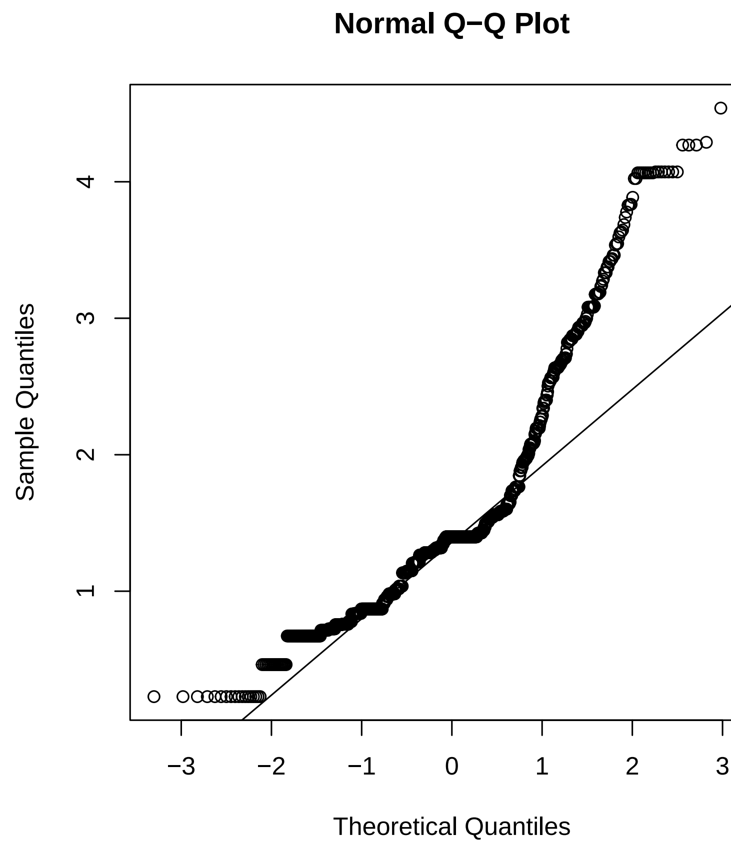
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality for each target.

```
mardia(db_rm[,c("greedy_1", "greedy_2", "greedy_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("greedy_1", "greedy_2", "greedy_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 2.25 skew = 391.8 with probability <= 0.00000000000000000000000000000000000000000000000000000000000000000000000000052
small sample skew = 393.5 with probability <= 0.0000000000000000000000000000000000000000000000

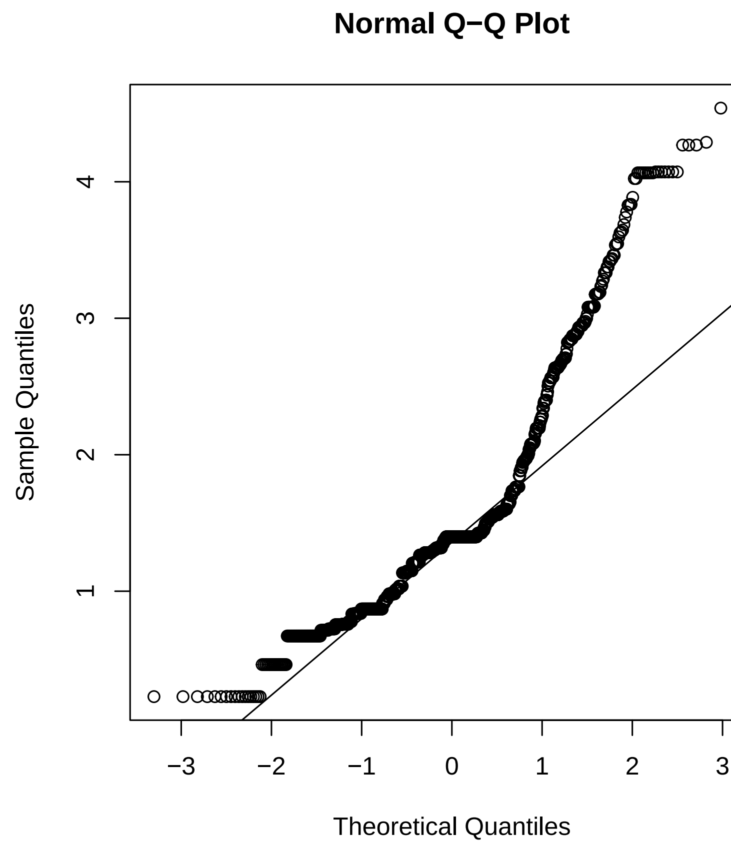


b2p = 20.86 kurtosis = 17.28 with probability <= 0

```r
mardia(db_rm[,c("greedy_1", "greedy_2", "greedy_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("greedy_1", "greedy_2", "greedy_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 2.25 skew = 391.8 with probability <= 0.000000000000000000000000000000000000000000000000000000000000000000000000052 small sample skew = 393.5 with probability <= 0.0000000000000000000000000000000000000000000000000



b2p = 20.86 kurtosis = 17.28 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  greedy_disp =~ greedy_1 + greedy_2 + greedy_3
   '

# estimation
# overall
m12_cfa_rm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)
```

```r
m12_cfa_rw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

# argentina
m12_cfa_rm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m12_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile
m12_cfa_rm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m12_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia
m12_cfa_rm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```r
m12_cfa_rw_col <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "4.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)


# españa
m12_cfa_rm_esp <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "9.Rich.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)


m12_cfa_rw_esp <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "9.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)


# mexico
m12_cfa_rm_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Rich.Men"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)


m12_cfa_rw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Rich.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)
```

```r
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9
```

```
bind_rows(
cfa_tab_fit(
  models = list(m12_cfa_rm, m12_cfa_rm_arg, m12_cfa_rm_cl, m12_cfa_rm_col, m12_cfa_rm_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Men")
,
cfa_tab_fit(
  models = list(m12_cfa_rw, m12_cfa_rw_arg, m12_cfa_rw_cl, m12_cfa_rw_col, m12_cfa_rw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 47: Summary fit indices of Greedy dispositions

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Men	1043	ML	0 (0)	1	1	0 [0-0]	0	11385.705

Table 47: Summary fit indices of Greedy dispositions

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Rich Women	1056	ML	0 (0)	1	1	0 [0-0]	0	11755.575
Argentina	Rich Men	216	ML	0 (0)	1	1	0 [0-0]	0	2339.979
	Rich Women	207	ML	0 (0)	1	1	0 [0-0]	0	2300.126
Chile	Rich Men	217	ML	0 (0)	1	1	0 [0-0]	0	2407.232
	Rich Women	223	ML	0 (0)	1	1	0 [0-0]	0	2456.741
Colombia	Rich Men	206	ML	0 (0)	1	1	0 [0-0]	0	2294.079
	Rich Women	199	ML	0 (0)	1	1	0 [0-0]	0	2323.775
Spain	Rich Men	195	ML	0 (0)	1	1	0 [0-0]	0	1972.255
	Rich Women	212	ML	0 (0)	1	1	0 [0-0]	0	2138.112
México	Rich Men	209	ML	0 (0)	1	1	0 [0-0]	0	2325.053
	Rich Women	215	ML	0 (0)	1	1	0 [0-0]	0	2432.016

5.4.14 Punishment rich

X

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("punish_1", "punish_2", "punish_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
```

```r
psych::describe(db_rw[,c("punish_1", "punish_2", "punish_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
) %>%
  mutate(vars = paste0("punish_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 48: Descriptive statistics of Punishment rich

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	punish_1	1043	5.415	1.932	6	5.739	1.483	1	7	6	-1.011	-0.167	0.060
	punish_2	1043	6.066	1.493	7	6.376	0.000	1	7	6	-1.662	2.072	0.046
	punish_3	1043	6.212	1.394	7	6.521	0.000	1	7	6	-1.800	2.464	0.043
Rich Women	punish_1	1056	4.420	2.219	4	4.524	2.965	1	7	6	-0.290	-1.292	0.068
	punish_2	1056	5.648	1.784	7	5.975	0.000	1	7	6	-1.210	0.447	0.055
	punish_3	1056	6.127	1.522	7	6.466	0.000	1	7	6	-1.817	2.524	0.047

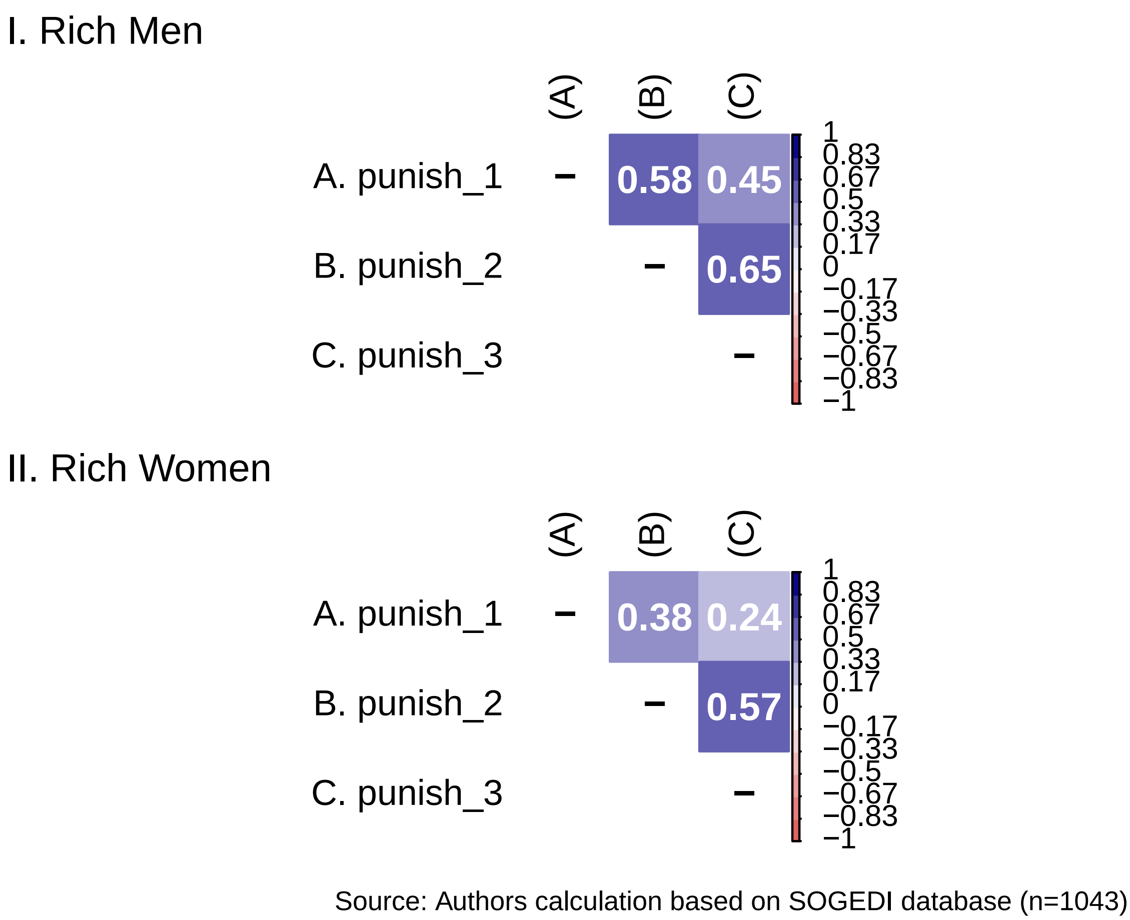
```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rm, c("punish_1", "punish_2", "punish_3")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      rect.col = "black",
      addCoef.col = "white",
      cl.cex = 0.8,
      cl.align.text = 'l',
```

```r
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_rw, c("punish_1", "punish_2", "punish_3")),
      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. Rich Women")




p1/p2 +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=1043)"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 22: Correlation matrix of Punishment rich



Reliability

```r
mi_variable <- "punish"
result2 <- alphas(db_proc, c("punish_1", "punish_2", "punish_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7030876
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   5.000   6.000   5.646   7.000   7.000    2110 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("punish_1", "punish_2", "punish_3")], n
```

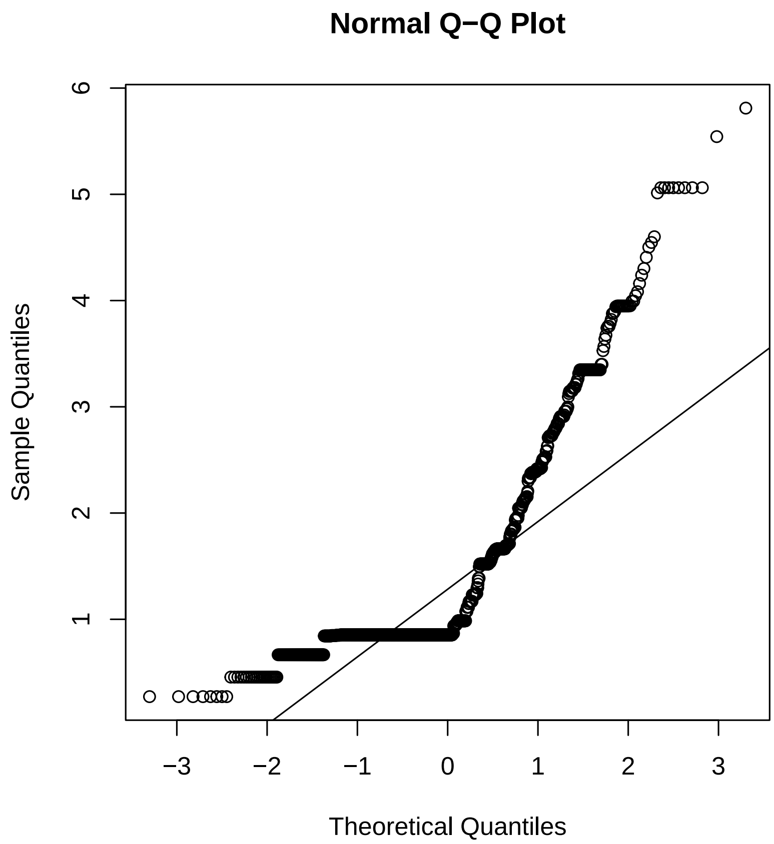
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality for each target.

```
mardia(db_rm[,c("punish_1", "punish_2", "punish_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("punish_1", "punish_2", "punish_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 9.22 skew = 1602.41 with probability <= 0 small sample skew = 1609.34 with probability <= 0 b2p = 28.41 kurtosis = 39.53 with

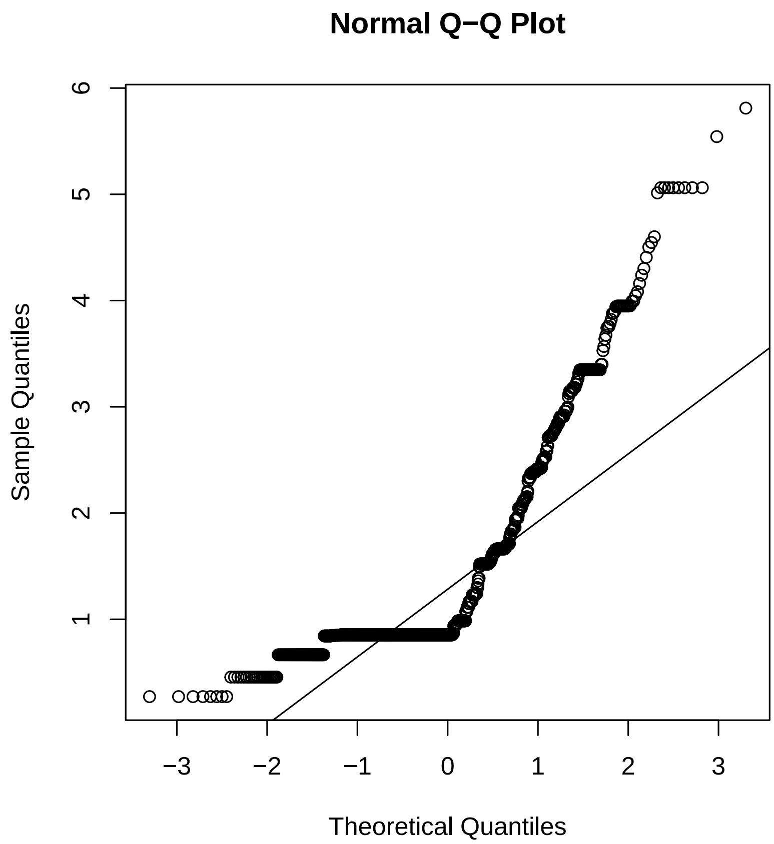


probability <= 0

```
mardia(db_rm[,c("punish_1", "punish_2", "punish_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("punish_1", "punish_2", "punish_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 3 b1p = 9.22 skew = 1602.41 with probability <= 0 small sample skew = 1609.34 with probability <= 0 b2p = 28.41 kurtosis = 39.53 with



probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  punishment =~ punish_1 + punish_2 + punish_3
   '

# estimation
# overall
m13_cfa_rm <- cfa(model = model_cfa,
                  data = subset(db_proc, target == "Rich.Men"),
                  estimator = "MLR",
                  ordered = F,
                  std.lv = F)
```

```r
m13_cfa_rw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

# argentina
m13_cfa_rm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m13_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile
m13_cfa_rm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m13_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia
m13_cfa_rm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```r
m13_cfa_rw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


# españa
m13_cfa_rm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m13_cfa_rw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


# mexico
m13_cfa_rm_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m13_cfa_rw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```r
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9
```

```r
bind_rows(
cfa_tab_fit(
  models = list(m13_cfa_rm, m13_cfa_rm_arg, m13_cfa_rm_cl, m13_cfa_rm_col, m13_cfa_rm_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Men")
,
cfa_tab_fit(
  models = list(m13_cfa_rw, m13_cfa_rw_arg, m13_cfa_rw_cl, m13_cfa_rw_col, m13_cfa_rw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 49: Summary fit indices of Punishment rich

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Men	1043	ML	0 (0)	1	1	0 [0-0]	0	10781.580

Table 49: Summary fit indices of Punishment rich

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
	Rich Women	1056	ML	0 (0)	1	1	0 [0-0]	0	12218.219
Argentina	Rich Men	216	ML	0 (0)	1	1	0 [0-0]	0	2329.549
	Rich Women	207	ML	0 (0)	1	1	0 [0-0]	0	2491.412
Chile	Rich Men	217	ML	0 (0)	1	1	0 [0-0]	0	2074.506
	Rich Women	223	ML	0 (0)	1	1	0 [0-0]	0	2539.111
Colombia	Rich Men	206	ML	0 (0)	1	1	0 [0-0]	0	2202.810
	Rich Women	199	ML	0 (0)	1	1	0 [0-0]	0	2285.530
Spain	Rich Men	195	ML	0 (0)	1	1	0 [0-0]	0	1929.482
	Rich Women	212	ML	0 (0)	1	1	0 [0-0]	0	2346.049
México	Rich Men	209	ML	0 (0)	1	1	0 [0-0]	0	2142.628
	Rich Women	215	ML	0 (0)	1	1	0 [0-0]	0	2524.644

5.5 Block 5. Atributions

5.5.1 Atributtions about poverty

We use the items with higher loading on each factor from the Spanish adaptation of the poverty and wealth attributions scales based on Sainz et al. (2023).

Descriptive analysis

```r
bind_rows(
psych::describe(db_pm[,c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_pw[,c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = case_when(vars <= 2 ~ paste0("ex_po_", vars),
                          vars >= 3 ~ paste0("in_po_", vars))) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 50: Descriptive statistics of Atributtions about poverty

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Poor Men	ex_po_1	1058	5.141	1.608	5	5.311	1.483	1	7	6	-0.657	-0.172	0.049
	ex_po_2	1058	4.917	1.746	5	5.091	1.483	1	7	6	-0.551	-0.518	0.054
	in_po_3	1058	4.128	1.786	4	4.159	1.483	1	7	6	-0.082	-0.841	0.055
	in_po_4	1058	4.421	1.930	4	4.525	2.965	1	7	6	-0.303	-0.951	0.059
Poor Women	ex_po_1	1052	5.201	1.646	5	5.391	1.483	1	7	6	-0.746	-0.123	0.051
	ex_po_2	1052	4.971	1.740	5	5.156	1.483	1	7	6	-0.617	-0.456	0.054
	in_po_3	1052	3.557	1.844	4	3.468	1.483	1	7	6	0.199	-0.923	0.057
	in_po_4	1052	4.211	1.982	4	4.264	2.965	1	7	6	-0.176	-1.091	0.061

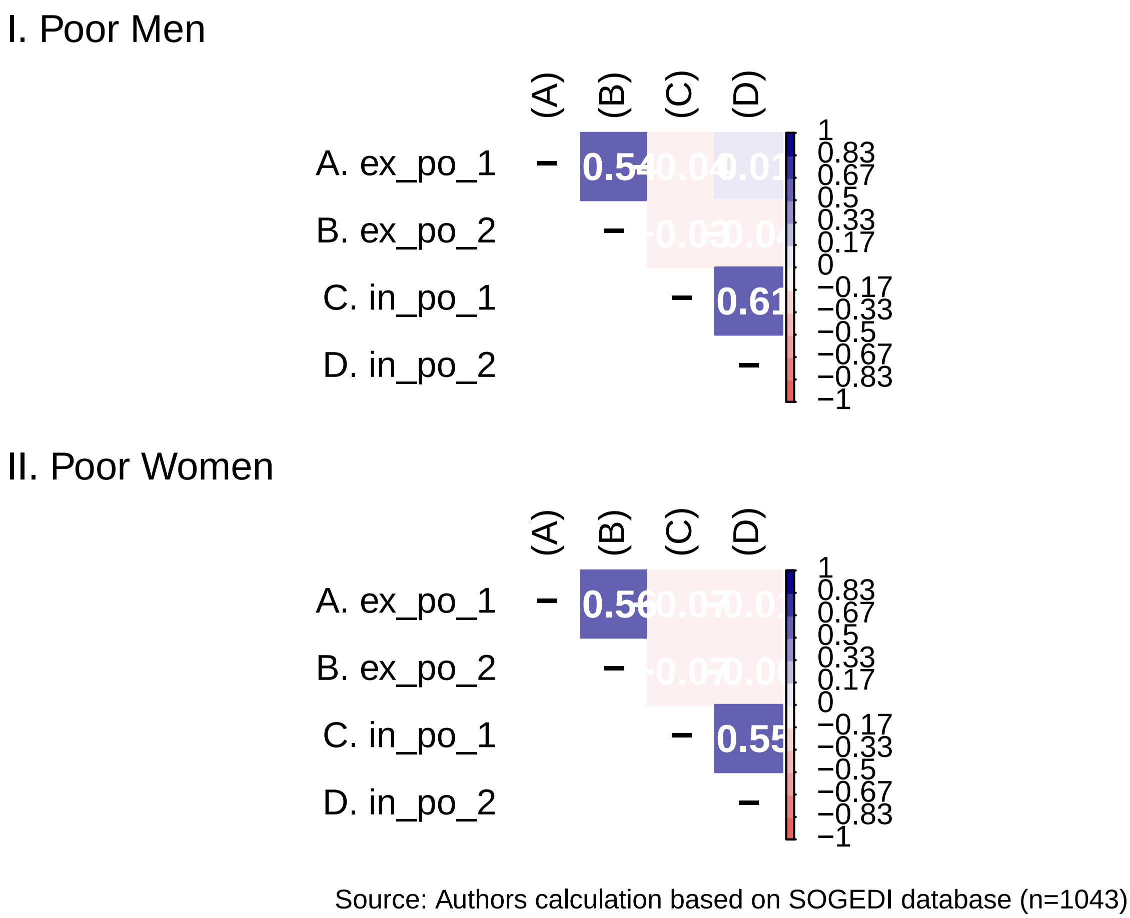
```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")),
```

```
      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. Poor Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")),
      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. Poor Women")




p1/p2 +
```

```r
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=1043)"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"

Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 23: Correlation matrix of Atributtions about poverty



Reliability

```
mi_variable <- "ex_atri_po"
result2 <- alphas(db_proc, c("ex_po_1", "ex_po_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.709259
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   4.000   5.000   5.057   6.500   7.000    2099 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("ex_po_1", "ex_po_2")], na.rm = TRUE)
```

```
mi_variable <- "in_atri_po"
result3 <- alphas(db_proc, c("in_po_1", "in_po_2"), mi_variable)

result3$raw_alpha
```

```
[1] 0.7319118
```

```
result3$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   1.00    3.00    4.00    4.08    5.50    7.00    2099 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("in_po_1", "in_po_2")], na.rm = TRUE)
```

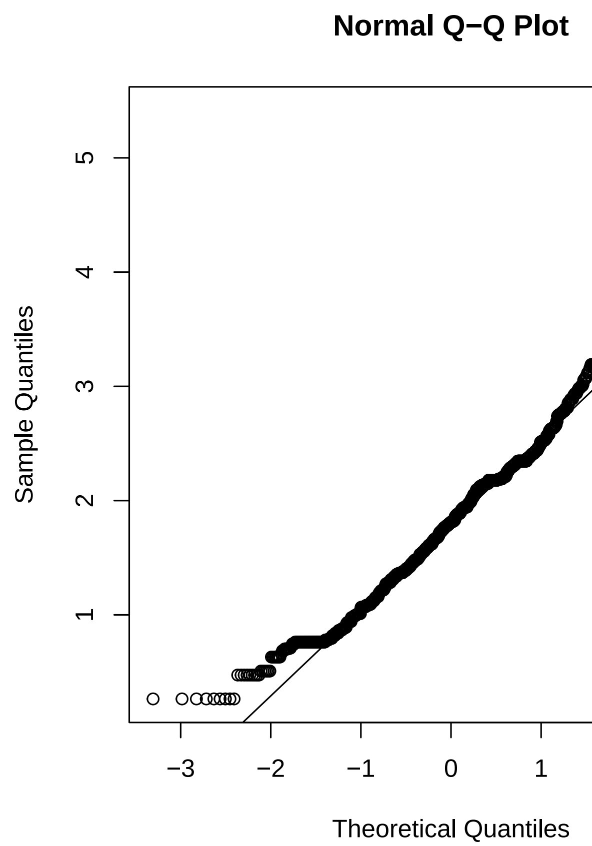
Confirmatory factor analysis

Mardia’s test for evaluate multivariate normality for each target.

```r
mardia(db_pm[,c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pm[, c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1058 num.vars = 4 b1p = 1.61 skew = 283.02 with probability <= 0.000000000000000000000000000000000000000000023 small sample skew = 284.14 with probability <= 0.000000000000000000000000000000000000000000014 b2p =

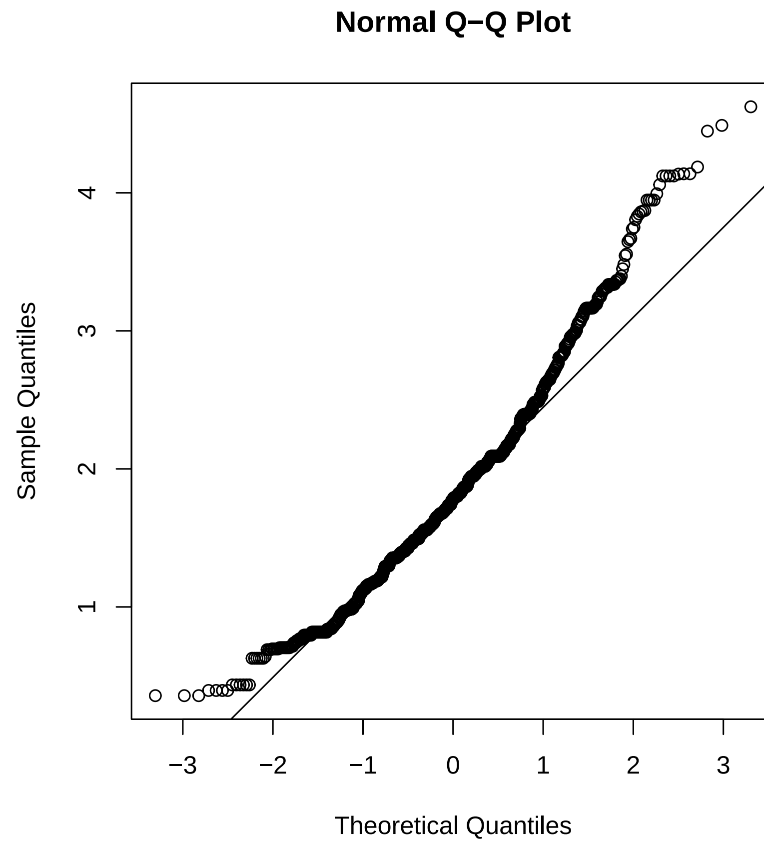


27.29 kurtosis = 7.73 with probability <= 0.000000000000011

```r
mardia(db_pw[,c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pw[, c("ex_po_1", "ex_po_2", "in_po_1", "in_po_2")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1052 num.vars = 4 b1p = 1.5 skew = 263.86 with probability <= 0.0000000000000000000000000000000000000000000018 small sample skew = 264.91 with probability <= 0.0000000000000000000000000000000000000000000011 b2p = 26.82 kurtosis = 6.61 with probability <= 0.000000000039



We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```
# model
#model_cfa <- '
#  external_atri_po =~ ex_po_1 + ex_po_2
#  internal_atri_po =~ in_po_1 + in_po_2
#'
#
## estimation
## overall
```

```
#m14_cfa_pm <- cfa(model = model_cfa,
#              data = subset(db_proc, target == "Poor.Men"),
#              estimator = "MLR",
#              ordered = F,
#              std.lv = F)
#
#m14_cfa_pw <- cfa(model = model_cfa,
#              data = subset(db_proc, target == "Poor.Women"),
#              estimator = "MLR",
#              ordered = F,
#              std.lv = F)
#
## argentina
#m14_cfa_pm_arg <- cfa(model = model_cfa,
#                 data = subset(db_proc, group == "1.Poor.Men"),
#                 estimator = "MLR",
#                 ordered = F,
#                 std.lv = F)
#
#m14_cfa_pw_arg <- cfa(model = model_cfa,
#                 data = subset(db_proc, group == "1.Poor.Women"),
#                 estimator = "MLR",
#                 ordered = F,
#                 std.lv = F)
#
## chile
#m14_cfa_pm_cl <- cfa(model = model_cfa,
#                     data = subset(db_proc, group == "3.Poor.Men"),
#                     estimator = "MLR",
#                     ordered = F,
#                     std.lv = F)
#
#
#m14_cfa_pw_cl <- cfa(model = model_cfa,
#                     data = subset(db_proc, group == "3.Poor.Women"),
#                     estimator = "MLR",
#                     ordered = F,
#                     std.lv = F)
#
## colombia
```

```
#m14_cfa_pm_col <- cfa(model = model_cfa,
#                      data = subset(db_proc, group == "4.Poor.Men"),
#                      estimator = "MLR",
#                      ordered = F,
#                      std.lv = F)
#
#
#m14_cfa_pw_col <- cfa(model = model_cfa,
#                      data = subset(db_proc, group == "4.Poor.Women"),
#                      estimator = "MLR",
#                      ordered = F,
#                      std.lv = F)
#
#
## españa
#m14_cfa_pm_esp <- cfa(model = model_cfa,
#                      data = subset(db_proc, group == "9.Poor.Men"),
#                      estimator = "MLR",
#                      ordered = F,
#                      std.lv = F)
#
#
#m14_cfa_pw_esp <- cfa(model = model_cfa,
#                      data = subset(db_proc, group == "9.Poor.Women"),
#                      estimator = "MLR",
#                      ordered = F,
#                      std.lv = F)
#
#
## mexico
#m14_cfa_pm_mex <- cfa(model = model_cfa,
#                      data = subset(db_proc, group == "13.Poor.Men"),
#                      estimator = "MLR",
#                      ordered = F,
#                      std.lv = F)
#
#
#m14_cfa_pw_mex <- cfa(model = model_cfa,
#                      data = subset(db_proc, group == "13.Poor.Women"),
#                      estimator = "MLR",
```

```
#                         ordered = F,
#                         std.lv = F)
#
```

5.5.2 Atributtions about wealth

We use the items with higher loading on each factor from the Spanish adaptation of the poverty and wealth attributions scales based on Sainz et al. (2023).

Descriptive analysis

```
bind_rows(
psych::describe(db_rm[,c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Men")
,
psych::describe(db_rw[,c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
) %>%
  mutate(vars = case_when(vars <= 2 ~ paste0("ex_we_", vars),
                          vars >= 3 ~ paste0("in_we_", vars))) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 52: Descriptive statistics of Atributtions about wealth

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Men	ex_we_1	1043	5.957	1.300	6	6.166	1.483	1	7	6	-1.284	1.318	0.040
	ex_we_2	1043	5.881	1.440	6	6.137	1.483	1	7	6	-1.383	1.486	0.045
	in_we_1	1043	5.267	1.638	5	5.473	1.483	1	7	6	-0.821	0.043	0.051

Table 52: Descriptive statistics of Atributtions about wealth

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Rich Women	in_we_14	1043	4.997	1.731	5	5.178	1.483	1	7	6	-0.579	-0.462	0.054
	ex_we_11	1056	5.861	1.306	6	6.053	1.483	1	7	6	-1.181	1.150	0.040
	ex_we_12	1056	5.921	1.400	6	6.169	1.483	1	7	6	-1.485	1.975	0.043
	in_we_13	1056	5.090	1.681	5	5.284	1.483	1	7	6	-0.698	-0.214	0.052
	in_we_14	1056	4.843	1.752	5	5.001	1.483	1	7	6	-0.482	-0.592	0.054

```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rm, c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")),
      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. Rich Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_rw, c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
```

Table 51: Summary fit indices of Atributtions about poverty

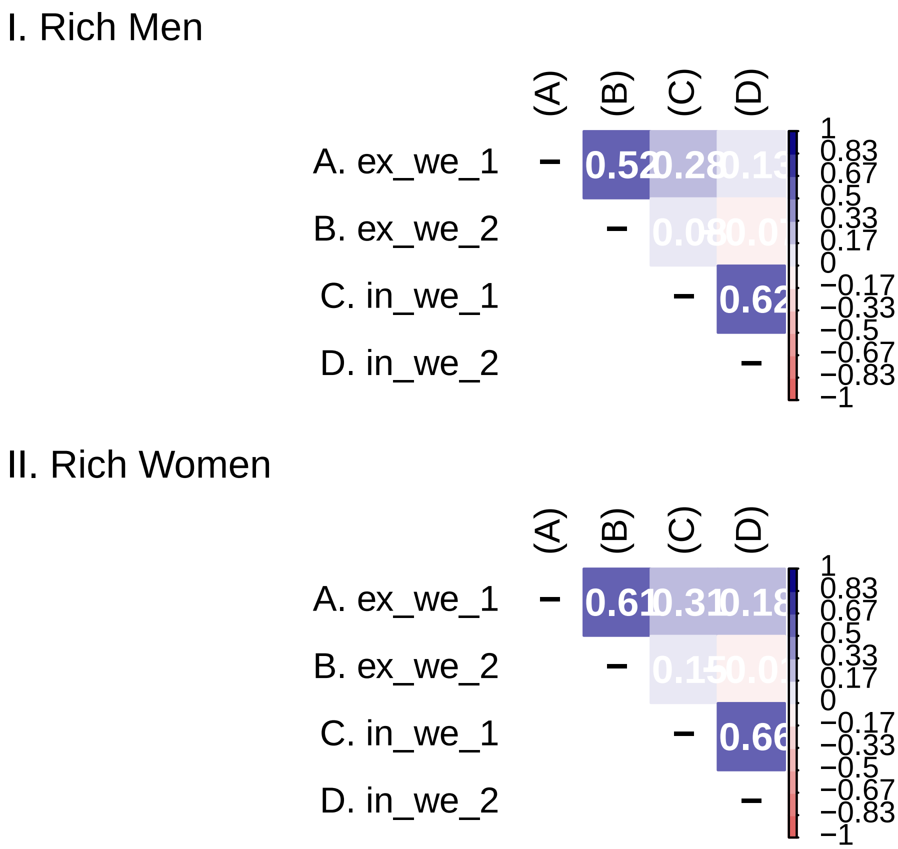
```
#colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ #(df)","CFI","TLI","RMSEA
#
#
#bind_rows(
#cfa_tab_fit(
#  models = list(m14_cfa_pm, m14_cfa_pm_arg, m14_cfa_pm_cl, #m14_cfa_pm_col, m14_cfa_p
#  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", #"Spain", "Mé
#)$sum_fit %>%
#  mutate(target = "Poor Men")
#,
#cfa_tab_fit(
#  models = list(m14_cfa_pw, m14_cfa_pw_arg, m14_cfa_pw_cl, #m14_cfa_pw_col, m14_cfa_p
#  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", #"Spain", "Mé
#)$sum_fit %>%
#  mutate(target = "Poor Women")
#) %>%
#  select(country, target, everything()) %>%
#  mutate(country = factor(country, levels = c("Overall scores", #"Argentina", "Chile"
#  group_by(country) %>%
#  arrange(country) %>%
#  mutate(country = if_else(duplicated(country), NA, country)) %>%
#  kableExtra::kable(
#  format     = "markdown",
#  digits     = 3,
#  booktabs   = TRUE,
#  col.names  = colnames_fit,
#  caption    = NULL
#) %>%
#  kableExtra::kable_styling(
#    full_width        = TRUE,
#    font_size         = 11,
#    latex_options     = "HOLD_position",
#    bootstrap_options = c("striped", "bordered")
#  ) %>%
#  kableExtra::collapse_rows(columns = 1)
```

```
      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. Rich Women")




p1/p2 +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI",
        " database (n=1043)"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 24: Correlation matrix of Atributtions about wealth



Source: Authors calculation based on SOGEDI database (n=1043)

Reliability

```r
mi_variable <- "ex_atri_we"
result2 <- alphas(db_proc, c("ex_we_1", "ex_we_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7187958
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   5.000   6.000   5.905   7.000   7.000    2110 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("ex_we_1", "ex_we_2")], na.rm = TRUE)
```

```
mi_variable <- "in_atri_we"
result3 <- alphas(db_proc, c("in_we_1", "in_we_2"), mi_variable)

result3$raw_alpha
```

```
[1] 0.7803945
```

```
result3$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   4.000   5.000   5.049   6.000   7.000    2110 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("in_we_1", "in_we_2")], na.rm = TRUE)
```

Confirmatory factor analysis

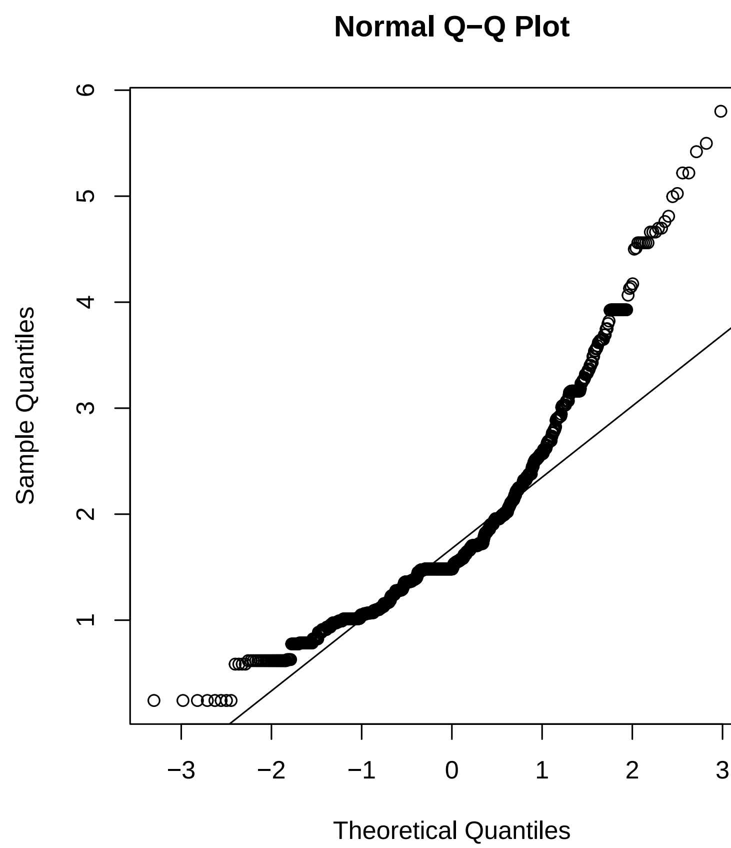
Mardia's test for evaluate multivariate normality for each target.

```
mardia(db_rm[,c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rm[, c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1043 num.vars = 4 b1p = 5.84 skew = 1014.66 with probability <= 0.00000000000000000000000000000000000000000000000000000000000000000000000000000000000

small sample skew = 1018.75 with probability <= 0.000000000000000000000000000000000000000000

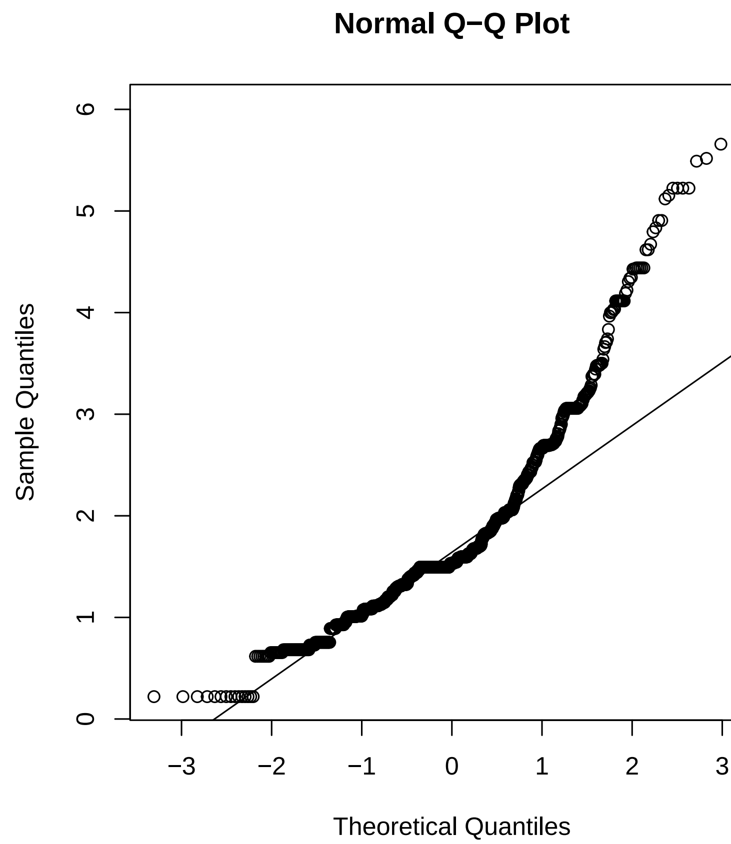


b2p = 35.88 kurtosis = 27.69 with probability <= 0

```
mardia(db_rw[,c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_rw[, c("ex_we_1", "ex_we_2", "in_we_1", "in_we_2")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1056 num.vars = 4 b1p = 5.26 skew = 926.15 with probability <= 0.0000000000000000000000000000000000000000000000000000000000000000000000000000000000000000000 small sample skew = 929.84 with probability <= 0.000000000000000000000000000000000000000000



b2p = 36.67 kurtosis = 29.71 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  external_atri_we =~ ex_we_1 + ex_we_2
  internal_atri_we =~ in_we_1 + in_we_2
'

# estimation
# overall
m15_cfa_rm <- cfa(model = model_cfa,
                  data = subset(db_proc, target == "Rich.Men"),
                  estimator = "MLR",
                  ordered = F,
```

```
              std.lv = F)

m15_cfa_rw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

# argentina
m15_cfa_rm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m15_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile
m15_cfa_rm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m15_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia
m15_cfa_rm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
```

```
                     std.lv = F)


m15_cfa_rw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


# españa
m15_cfa_rm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m15_cfa_rw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


# mexico
m15_cfa_rm_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m15_cfa_rw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m15_cfa_rm, m15_cfa_rm_cl, m15_cfa_rm_col, m15_cfa_rm_esp, m15_cfa_rm_
  country_names = c("Overall scores", "Chile", "Colombia", "Spain", "México")
)$sum_fit %>%
  mutate(target = "Rich Men")
,
cfa_tab_fit(
  models = list(m15_cfa_rw, m15_cfa_rw_arg, m15_cfa_rw_cl, m15_cfa_rw_col, m15_cfa_rw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 53: Summary fit indices of Atributtions about wealth

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Men	1043	ML	24.221 (1) ***	0.975	0.853	0.149 [0.101-0.203]	0.040	14406.862
	Rich Women	1056	ML	30.881 (1) ***	0.976	0.853	0.168 [0.12-0.222]	0.035	14360.205
Argentina	Rich Women	207	ML	5.55 (1) *	0.981	0.883	0.148 [0.049-0.278]	0.035	2807.519
Chile	Rich Men	217	ML	4.044 (1) *	0.988	0.927	0.118 [0.016-0.248]	0.034	2992.819
	Rich Women	223	ML	20.83 (1) ***	0.923	0.539	0.298 [0.195-0.416]	0.056	3067.145
Colombia	Rich Men	206	ML	0.143 (1)	1.000	1.029	0 [0-0.134]	0.006	2790.397
	Rich Women	199	ML	1.171 (1)	0.999	0.994	0.029 [0-0.193]	0.017	2672.028
Spain	Rich Men	195	ML	8.567 (1) **	0.969	0.814	0.197 [0.092-0.327]	0.066	2509.596
	Rich Women	212	ML	3.819 (1) .	0.992	0.954	0.115 [0-0.247]	0.024	2689.485
México	Rich Men	209	ML	8.055 (1) **	0.958	0.746	0.184 [0.083-0.31]	0.050	2998.907
	Rich Women	215	ML	1.164 (1)	0.999	0.995	0.028 [0-0.186]	0.016	3025.332

5.6 Block 6. Stereotypes

5.6.1 Thick skin bias

We reduced the amount of items that the original authors used and silly adapted to our context of study (Cheek & Shafir, 2024). We did not find any information regarding factorial analyses so we selected the items that were more likely to be applied to low-SES groups in our context.

Descriptive analysis

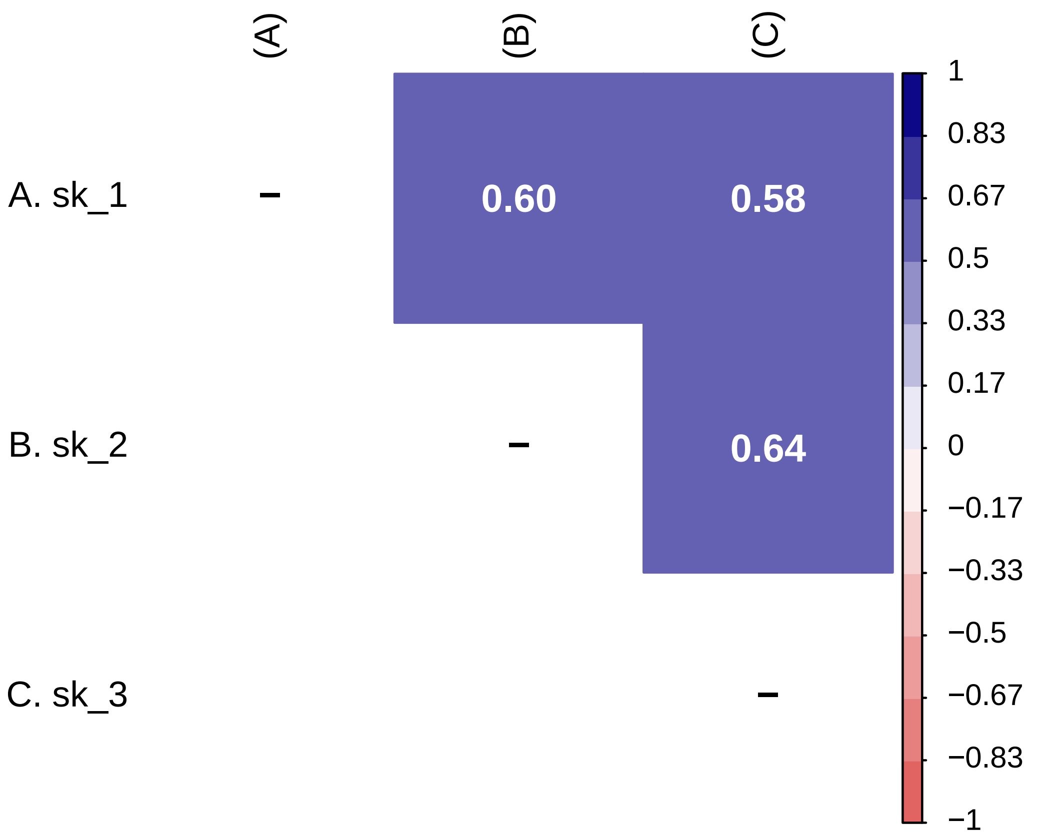
```r
describe_kable(db_proc, c("sk_1", "sk_2", "sk_3"))
```

Table 54: Descriptive statistics of Thick skin bias

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
sk_1	1	4209	5.292	1.773	6	5.533	1.483	1	7	6	-0.804	-0.305	0.027
sk_2	2	4209	5.540	1.748	6	5.828	1.483	1	7	6	-1.058	0.156	0.027
sk_3	3	4209	5.442	1.787	6	5.725	1.483	1	7	6	-0.975	-0.049	0.028

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("sk_1", "sk_2", "sk_3")),
      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"
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 25: Correlation matrix of Thick skin bias



Source: Authors calculation based on SOGEDI database

Reliability

```
mi_variable <- "skin"
result2 <- alphas(db_proc, c("sk_1", "sk_2", "sk_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8232648
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   4.333   5.667   5.424   7.000   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("sk_1", "sk_2", "sk_3")], na.rm = TRUE)
```

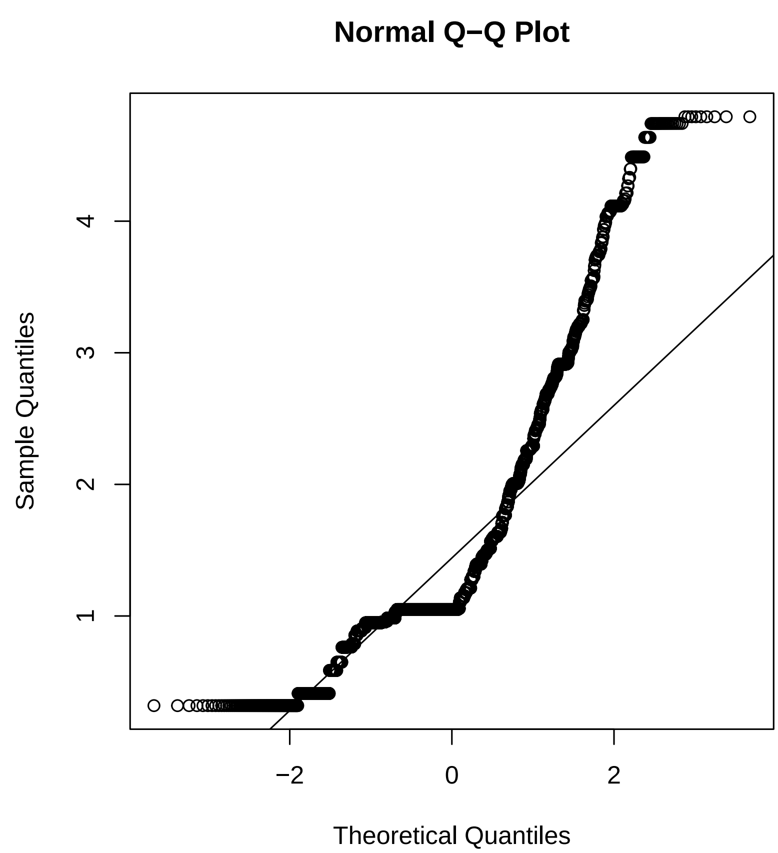
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality.

```r
mardia(db_proc[,c("sk_1", "sk_2", "sk_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("sk_1", "sk_2", "sk_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 3 b1p = 3.12 skew = 2188.55 with probability <= 0 small sample skew = 2190.89 with probability <= 0 b2p = 24.77 kurtosis = 57.84 with



probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  skin_bias =~ sk_1 + sk_2 + sk_3
'

# estimation
# overall
m16_cfa <- cfa(model = model_cfa,
              data = db_proc,
              estimator = "MLR",
              ordered = F,
              std.lv = F)

# argentina
m16_cfa_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, country_residence_recoded == 1),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile
m16_cfa_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, country_residence_recoded == 3),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


# colombia
m16_cfa_col <- cfa(model = model_cfa,
                     data = subset(db_proc, country_residence_recoded == 4),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```r
# españa
m16_cfa_esp <- cfa(model = model_cfa,
                      data = subset(db_proc, country_residence_recoded == 9),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)


# mexico
m16_cfa_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, country_residence_recoded == 13),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)
```

```r
cfa_tab_fit(
  models = list(m16_cfa, m16_cfa_arg, m16_cfa_cl, m16_cfa_col, m16_cfa_esp, m16_cfa_me
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$fit_table
```

Table 55: Summary fit indices of Thick skin bias

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	0 (0)	1	1	0 [0-0]	0	45672.145
Argentina	807	ML	0 (0)	1	1	0 [0-0]	0	8564.323
Chile	883	ML	0 (0)	1	1	0 [0-0]	0	9455.343
Colombia	833	ML	0 (0)	1	1	0 [0-0]	0	9437.460
Spain	835	ML	0 (0)	1	1	0 [0-0]	0	8238.133
México	846	ML	0 (0)	1	1	0 [0-0]	0	9547.576

5.6.2 Deservingness

Items adapted (own translation) from Meleuman, Roosma & Abts (2020). These items are uniquely presented for participants in the poverty condition.

Descriptive analysis

```r
db_proc$carin_control_2_r <- sjmisc::rec(db_proc$carin_control_2,rec = "rev")
db_pm$carin_control_2_r <- sjmisc::rec(db_pm$carin_control_2,rec = "rev")
db_pw$carin_control_2_r <- sjmisc::rec(db_pw$carin_control_2,rec = "rev")

bind_rows(
psych::describe(db_pm[,c("carin_control_1","carin_control_2_r","carin_attitude_1","car
    as_tibble() %>%
    mutate(target = "Poor Men")
,
psych::describe(db_pw[,c("carin_control_1","carin_control_2_r","carin_attitude_1","car
    as_tibble() %>%
    mutate(target = "Poor Women")
) %>%
  mutate(vars = case_when(vars %in% c(1:2) ~ paste0("carin_control_", vars),
                          vars %in% c(3:4) ~ paste0("carin_attitude_", vars),
                          vars %in% c(5:6) ~ paste0("carin_reciprocity_", vars),
                          vars %in% c(7:8) ~ paste0("carin_identity_", vars),
                          vars %in% c(9:10) ~ paste0("carin_need_", vars))) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 56: Descriptive statistics of Deservingness

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Poor Men	carin_control_1	1058	3.907	1.916	4	3.884	1.483	1	7	6	0.105	-0.990	0.059
	carin_control_2	1058	4.883	1.860	5	5.067	2.965	1	7	6	-0.503	-0.744	0.057
	carin_attitude_3	1058	4.466	1.988	4	4.581	2.965	1	7	6	-0.256	-1.052	0.061
	carin_attitude_4	1058	2.891	1.871	2	2.654	1.483	1	7	6	0.696	-0.574	0.058
	carin_reciprocity_5	1058	3.504	1.997	4	3.381	2.965	1	7	6	0.232	-1.095	0.061
	carin_reciprocity_6	1058	4.486	2.111	5	4.606	2.965	1	7	6	-0.386	-1.112	0.065

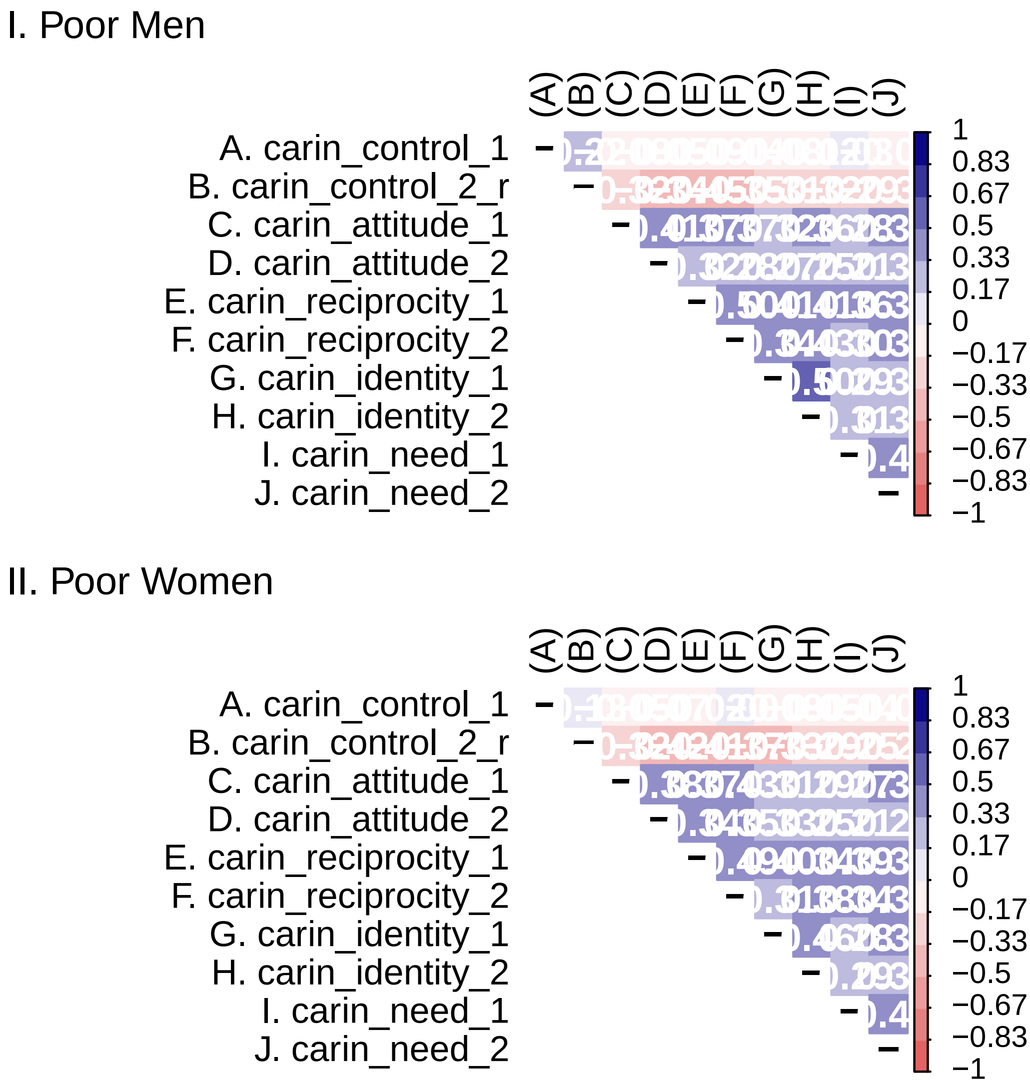
Table 56: Descriptive statistics of Deservingness

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
	carin_identity_7	1058	3.378	2.172	3	3.224	2.965	1	7	6	0.353	-1.251	0.067
	carin_identity_8	1058	4.678	2.223	5	4.846	2.965	1	7	6	-0.464	-1.209	0.068
	carin_need_9	1058	3.571	2.186	4	3.465	2.965	1	7	6	0.232	-1.334	0.067
	carin_need_10	1058	3.967	2.112	4	3.959	2.965	1	7	6	-0.029	-1.290	0.065
Poor Women	carin_control_1	1052	4.085	1.941	4	4.106	2.965	1	7	6	-0.017	-1.053	0.060
	carin_control_2	1052	5.585	1.659	6	5.846	1.483	1	7	6	-1.012	0.155	0.051
	carin_attitude_3	1052	4.087	2.036	4	4.109	2.965	1	7	6	-0.106	-1.133	0.063
	carin_attitude_4	1052	2.656	1.838	2	2.380	1.483	1	7	6	0.868	-0.311	0.057
	carin_reciprocity_5	1052	3.104	1.951	3	2.904	2.965	1	7	6	0.495	-0.909	0.060
	carin_reciprocity_6	1052	3.954	2.158	4	3.943	2.965	1	7	6	-0.052	-1.340	0.067
	carin_identity_7	1052	2.950	2.069	2	2.692	1.483	1	7	6	0.662	-0.890	0.064
	carin_identity_8	1052	4.414	2.289	5	4.518	2.965	1	7	6	-0.284	-1.408	0.071
	carin_need_9	1052	3.471	2.217	3	3.340	2.965	1	7	6	0.312	-1.313	0.068
	carin_need_10	1052	3.794	2.144	4	3.742	2.965	1	7	6	0.096	-1.309	0.066

```
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pm, c("carin_control_1","carin_control_2_r","carin_
      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. Poor Men")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations_pairwise(db_pw, c("carin_control_1","carin_control_2_r","carin_
      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. Poor Women")


p1/p2 +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 26: Correlation matrix of Deservingness



Source: Authors calculation based on SOGEDI database

Reliability

```
mi_variable <- "carin_control"
result2 <- alphas(db_proc, c("carin_control_1","carin_control_2_r"), mi_variable)

result2$raw_alpha
```

```
[1] 0.3047283
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   4.000   4.500   4.614   5.500   7.000    2099 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("carin_control_1","carin_control_2_r")]
```

```r
mi_variable <- "carin_attitude"
result2 <- alphas(db_proc, c("carin_attitude_1","carin_attitude_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.5674176
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   2.500   3.500   3.526   4.500   7.000    2099 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("carin_attitude_1","carin_attitude_2")]
```

```r
mi_variable <- "carin_reciprocity"
result2 <- alphas(db_proc, c("carin_reciprocity_1","carin_reciprocity_2"), mi_variable

result2$raw_alpha
```

```
[1] 0.6654127
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   2.500   4.000   3.763   5.000   7.000    2099 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("carin_reciprocity_1","carin_reciprocit
```

```r
mi_variable <- "carin_identity"
result2 <- alphas(db_proc, c("carin_identity_1","carin_identity_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.6494677
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   2.500   4.000   3.856   5.500   7.000    2099 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("carin_identity_1","carin_identity_2")]
```

```r
mi_variable <- "carin_need"
result2 <- alphas(db_proc, c("carin_need_1","carin_need_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.6357058
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  1.000   2.000   4.000   3.701   5.000   7.000    2099 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("carin_need_1","carin_need_2")], na.rm
```

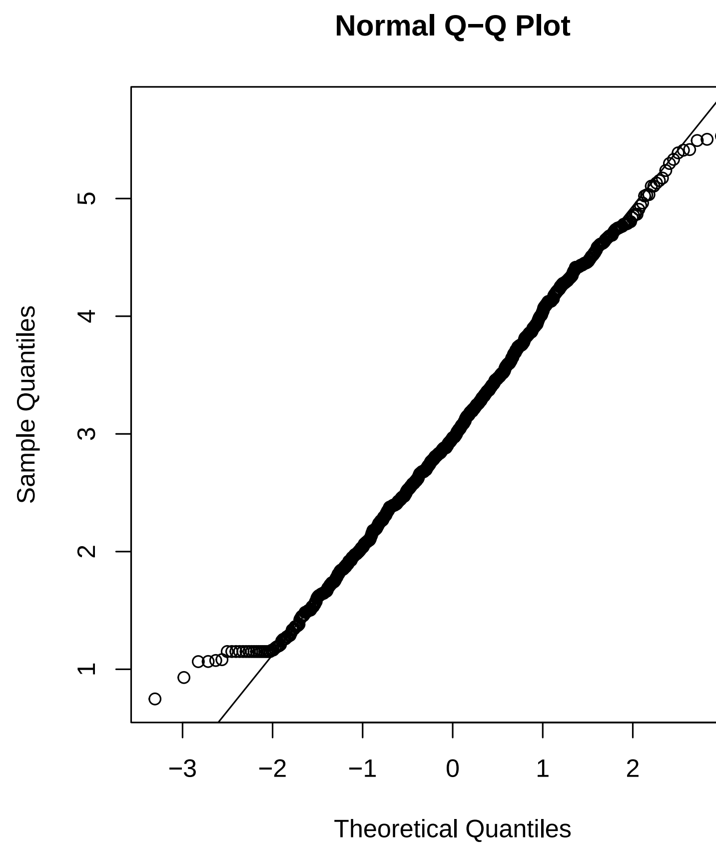
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality.

```
mardia(db_pm[,c("carin_control_1","carin_control_2_r","carin_attitude_1","carin_attitu
       na.rm = T, plot=T)
```

Call: mardia(x = db_pm[, c("carin_control_1", "carin_control_2_r", "carin_attitude_1", "carin_attitude_2", "carin_reciprocity_1", "carin_reciprocity_2", "carin_identity_1", "carin_identity_2", "carin_need_1", "carin_need_2")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1058 num.vars = 10 b1p = 4.9 skew = 864.84 with probability <= 0.0000000000000000000000000000000000000000000000000000000000000000000000000000003
small sample skew = 867.74 with probability <= 0.000000000000000000000000000000000000000000000000

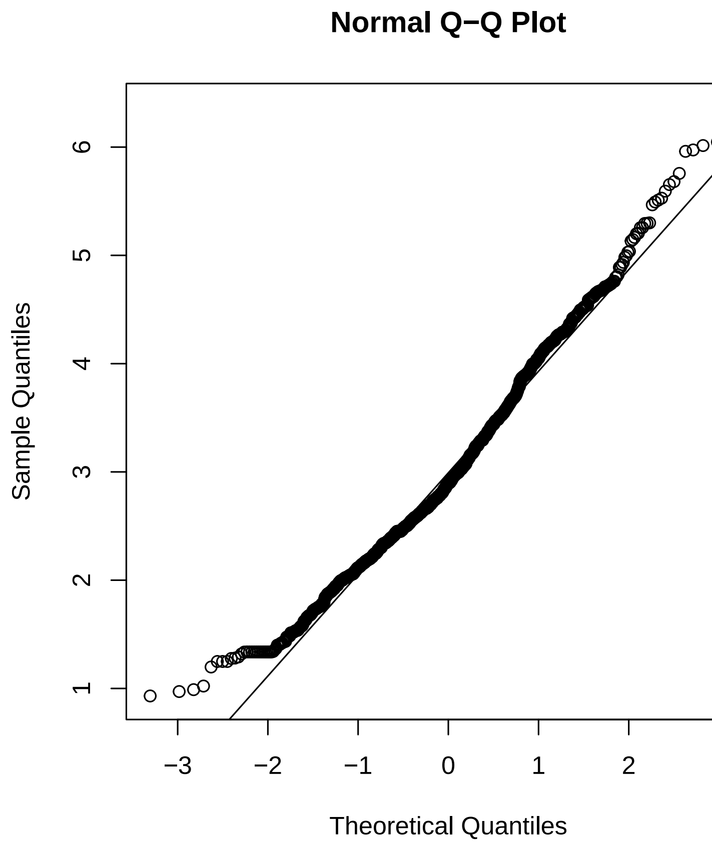


b2p = 134.56 kurtosis = 15.28 with probability <= 0

```
mardia(db_pw[,c("carin_control_1","carin_control_2_r","carin_attitude_1","carin_attitu
       na.rm = T, plot=T)
```

Call: mardia(x = db_pw[, c("carin_control_1", "carin_control_2_r", "carin_attitude_1", “carin_attitude_2”, “carin_reciprocity_1”, “carin_reciprocity_2”, “carin_identity_1”, “carin_identity_2”, “carin_need_1”, “carin_need_2”)], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1052 num.vars = 10 b1p = 6.14 skew = 1076.46 with probability <= 0.000000000000000000000000000000000000000000000000000000000000000000000000000000000
small sample skew = 1080.09 with probability <= 0.00000000000000000000000000000000000000000



b2p = 137.99 kurtosis = 18.83 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodnes of fit indicators are shown.

```
# model
model_cfa <- '
  control =~ carin_control_1 + carin_control_2_r
  attitude =~ carin_attitude_1 + carin_attitude_2
  reciprocity =~ carin_reciprocity_1 + carin_reciprocity_2
  identity =~ carin_identity_1 + carin_identity_2
```

```
  need =~ carin_need_1 + carin_need_2
'

# estimation
# overall
m17_cfa_pm <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Men"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m17_cfa_pw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

# argentina
m17_cfa_pm_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Men"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m17_cfa_pw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile
m17_cfa_pm_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m17_cfa_pw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Women"),
```

```
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia
m17_cfa_pm_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m17_cfa_pw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


# españa
m17_cfa_pm_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


m17_cfa_pw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)


# mexico
m17_cfa_pm_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Poor.Men"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```r
m17_cfa_pw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```r
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m17_cfa_pm, m17_cfa_pm_arg, m17_cfa_pm_esp, m17_cfa_pm_mex),
  country_names = c("Overall scores", "Argentina", "Spain", "México")
)$sum_fit %>%
  mutate(target = "Poor Men")
,
cfa_tab_fit(
  models = list(m17_cfa_pw, m17_cfa_pw_arg, m17_cfa_pw_cl, m17_cfa_pw_col, m17_cfa_pw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
```

```
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 57: Summary fit indices of Deservingness

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Poor Men	1058	ML	61.943 (25) ***	0.985	0.974	0.037 [0.026-0.049]	0.023	42659.995
	Poor Women	1052	ML	87.901 (25) ***	0.974	0.953	0.049 [0.038-0.06]	0.026	42347.411
Argentina	Poor Men	219	ML	32.865 (25)	0.985	0.972	0.038 [0-0.07]	0.034	8867.883
	Poor Women	215	ML	49.747 (25) **	0.960	0.929	0.068 [0.04-0.095]	0.046	8541.143
Chile	Poor Women	205	ML	48.715 (25) **	0.944	0.900	0.068 [0.039-0.096]	0.046	8430.931
Colombia	Poor Women	205	ML	39.816 (25) *	0.955	0.919	0.054 [0.017-0.084]	0.050	8262.347
Spain	Poor Men	213	ML	43.057 (25) *	0.980	0.964	0.058 [0.026-0.087]	0.029	8035.667
	Poor Women	211	ML	24 (25)	1.000	1.002	0 [0-0.053]	0.025	7891.841
México	Poor Men	197	ML	42.347 (25) *	0.962	0.931	0.059 [0.025-0.089]	0.046	8045.836
	Poor Women	216	ML	43.106 (25) *	0.953	0.915	0.058 [0.026-0.086]	0.043	8848.649

5.7 Block 7. Dehumanization

5.7.1 Blatant dehumanization

These items comes from the work of Kteily et al. (2015).

Descriptive analysis

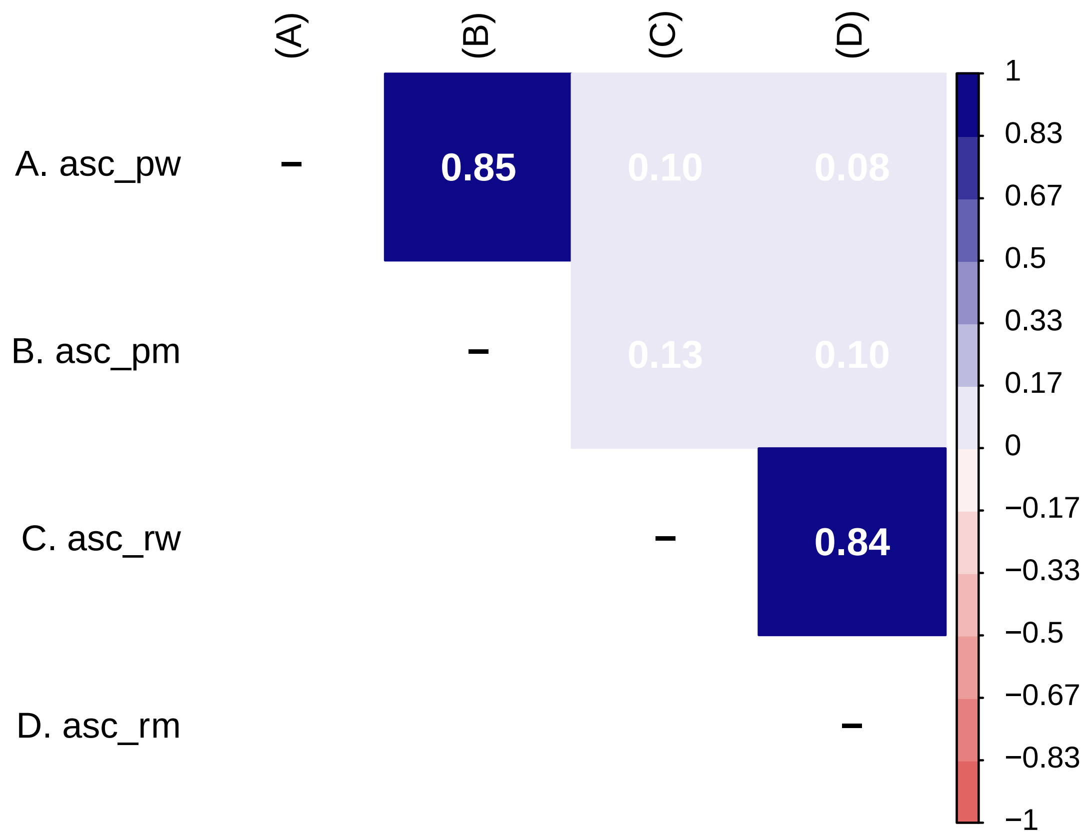
```r
describe_kable(db_proc, c("asc_pw", "asc_pm", "asc_rw", "asc_rm"))
```

Table 58: Descriptive statistics of Blatant dehumanization items

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
asc_pw	1	4209	53.148	21.871	51	52.536	20.756	0	100	100	0.208	-0.222	0.337
asc_pm	2	4209	51.533	21.893	50	50.868	20.756	0	100	100	0.252	-0.219	0.337
asc_rw	3	4209	66.552	21.785	70	67.838	23.722	0	100	100	-0.535	0.021	0.336
asc_rm	4	4209	67.434	21.854	70	68.893	23.722	0	100	100	-0.616	0.162	0.337

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("asc_pw", "asc_pm", "asc_rw", "asc_rm")),
      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"
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 27: Correlation matrix of Blatant dehumanization items



Source: Authors calculation based on SOGEDI database

5.8 Block 8. Sexuality

5.8.1 Perceived promiscuity of women

Items taken from Spencer's work (2016), we changed the response format to fit the survey.

Descriptive analysis

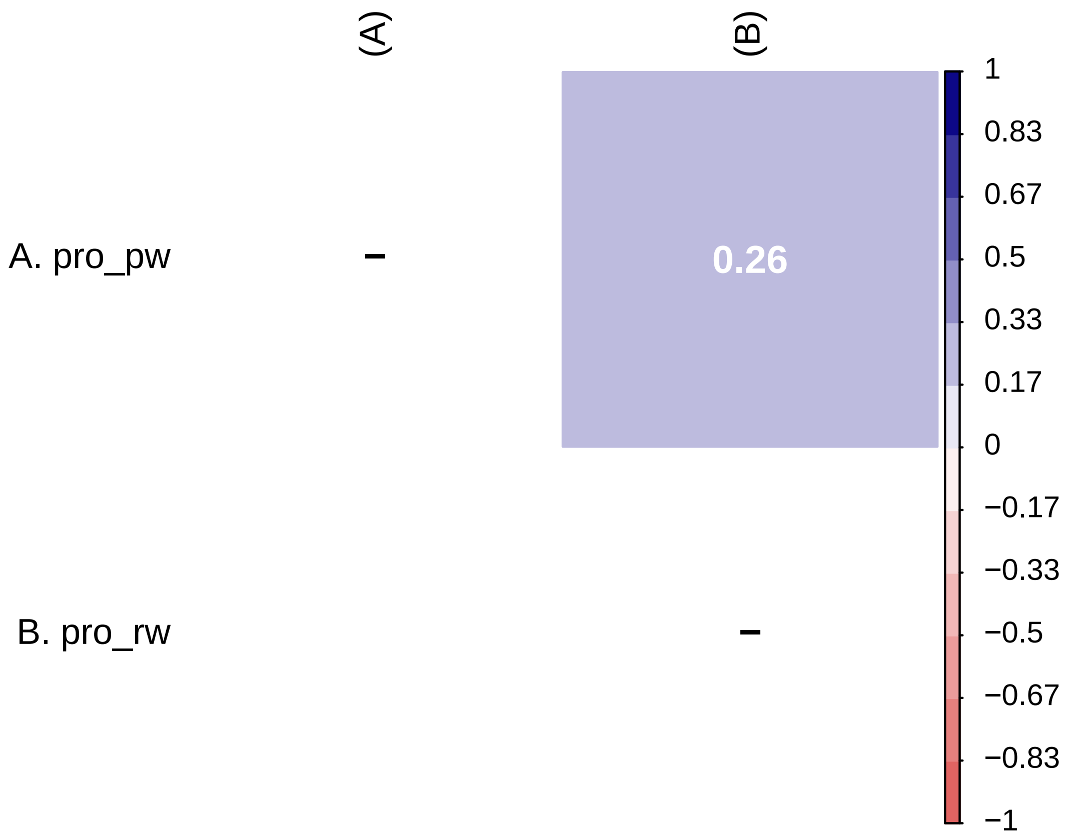
```
describe_kable(db_proc, c("pro_pw", "pro_rw"))
```

Table 59: Descriptive statistics of Perceived promiscuity of women

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
pro_pw	1	4209	3.854	1.674	4	3.846	1.483	1	7	6	-0.055	-0.577	0.026
pro_rw	2	4209	4.423	1.586	4	4.478	1.483	1	7	6	-0.258	-0.333	0.024

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("pro_pw", "pro_rw")),
      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"
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 28: Correlation matrix of Perceived promiscuity of women



Source: Authors calculation based on SOGEDI database

Reliability

```
mi_variable <- "pro"
result2 <- alphas(db_proc, c("pro_pw", "pro_rw"), mi_variable)

result2$raw_alpha
```

```
[1] 0.4154746
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.500   4.000   4.139   5.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("pro_pw", "pro_rw")], na.rm = TRUE)
```

5.8.2 Risk sexual behavior of women

In the literature, there are scales to measure this, but they are almost always from a personal perspective (evaluating the risk one takes). We used the scale provided in Raiford et al. (2014) paper to create this single item in order not to lengthen the scale too much.

Descriptive analysis

```
describe_kable(db_proc, c("ris_pw", "ris_rw"))
```

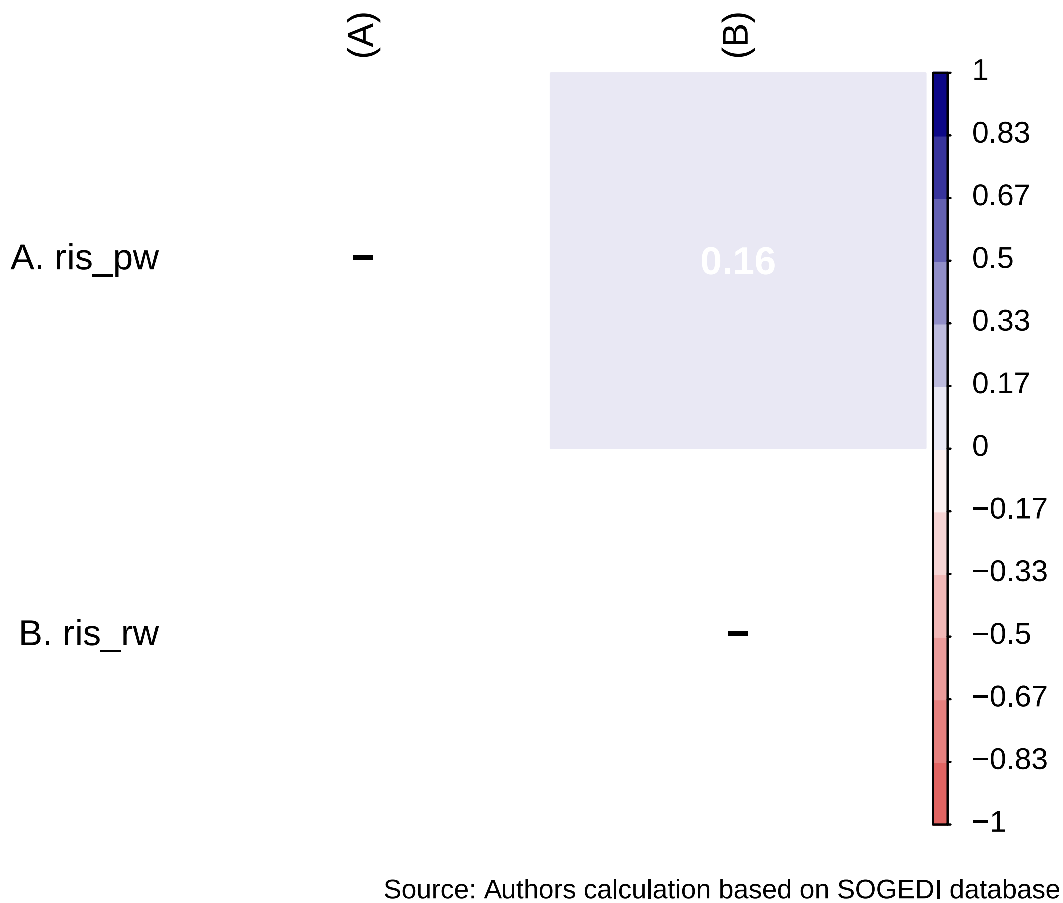
Table 60: Descriptive statistics of Risk sexual behavior of women

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
ris_pw	1	4209	5.042	1.590	5	5.189	1.483	1	7	6	-0.577	-0.208	0.025
ris_rw	2	4209	4.034	1.767	4	4.042	1.483	1	7	6	-0.001	-0.802	0.027

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("ris_pw", "ris_rw")),
      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"
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 29: Correlation matrix of Risk sexual behavior of women



Reliability

```r
mi_variable <- "ris"
result2 <- alphas(db_proc, c("ris_pw", "ris_rw"), mi_variable)

result2$raw_alpha
```

```
[1] 0.2747541
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   4.000   4.500   4.538   5.500   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("ris_pw", "ris_rw")], na.rm = TRUE)
```

5.8.3 Unplanned pregnancy of women

We have created this item, but we believe it could be interesting to explore the idea that poor women have children to take advantage of social assistance. ##### **Descriptive analysis**

```r
describe_kable(db_proc, c("pre_pw", "pre_rw"))
```

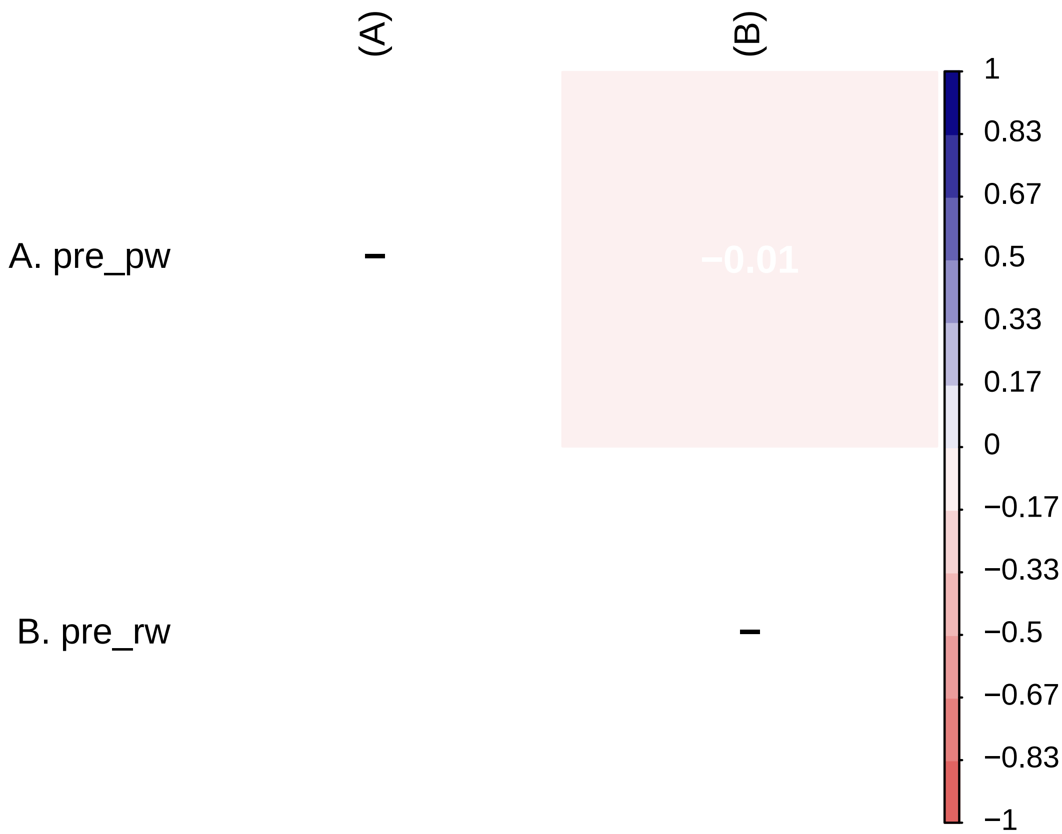
Table 61: Descriptive statistics of Unplanned pregnancy of women

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
pre_pw	1	4209	5.590	1.387	6	5.754	1.483	1	7	6	-0.887	0.404	0.021
pre_rw	2	4209	3.065	1.665	3	2.913	1.483	1	7	6	0.563	-0.323	0.026

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("pre_pw", "pre_rw")),
      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"
  )
) +
  plot_annotation(
    caption = paste0(
      "Source: Authors calculation based on SOGEDI database"
    )
  )
```

Figure 30: Correlation matrix of Unplanned pregnancy of women



Source: Authors calculation based on SOGEDI database

Reliability

```
mi_variable <- "pre"
result2 <- alphas(db_proc, c("pre_pw", "pre_rw"), mi_variable)
```

```
Some items ( pre_rw ) were negatively correlated with the total scale and
probably should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
```

```
result2$raw_alpha
```

```
[1] -0.01070256
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   4.000   4.000   4.327   5.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("pre_pw", "pre_rw")], na.rm = TRUE)
```

5.8.4 Abuse of social assistance by poor mothers

The items to measure this process are inspired by scales on teenage mothers but we adapted to capture attitudes towards the group of poor mothers based on our experience with similar scales (Kim et al., 2013).

Descriptive analysis

```
describe_kable(db_proc, c("wel_abu_1","wel_abu_2"))
```

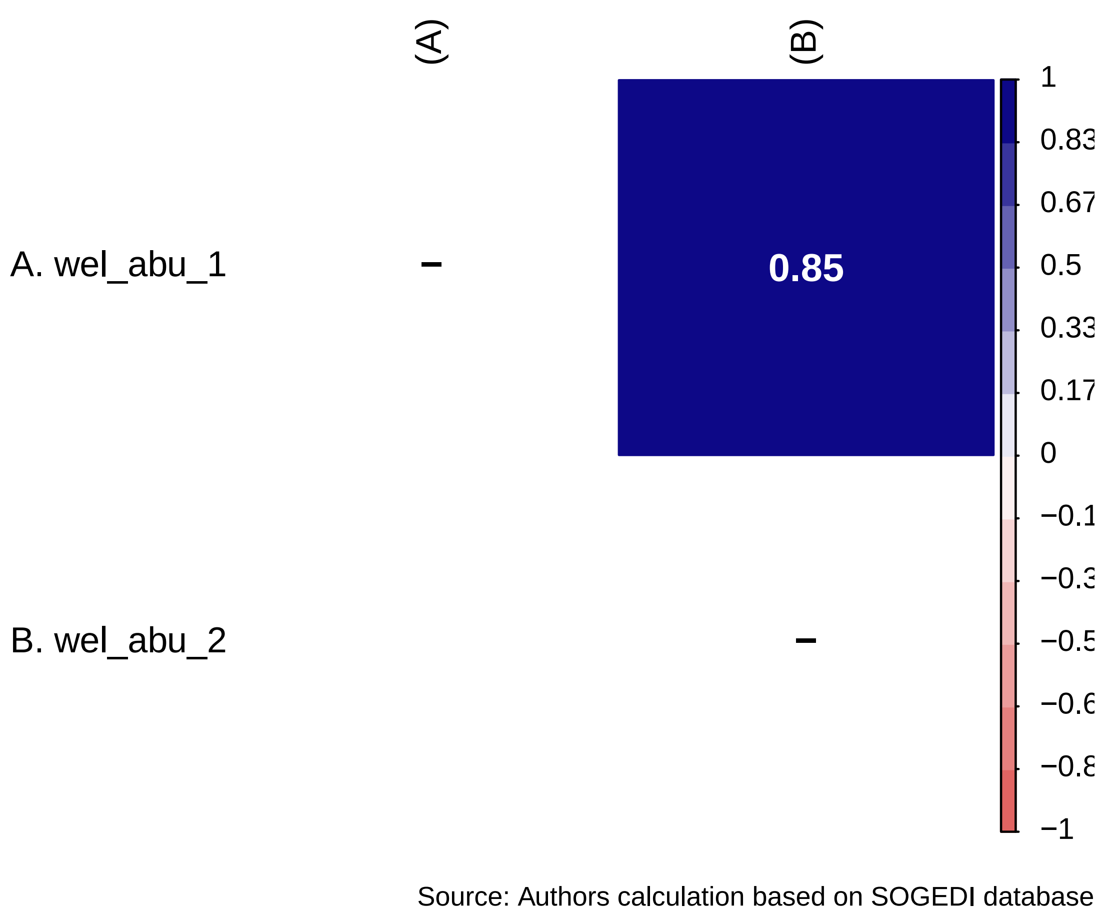
Table 62: Descriptive statistics of Abuse of social assistance by poor mothers

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
wel_abu_1	1	4209	3.545	2.008	4	3.431	2.965	1	7	6	0.214	-1.166	0.031
wel_abu_2	2	4209	3.547	1.996	4	3.434	2.965	1	7	6	0.192	-1.161	0.031

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("wel_abu_1","wel_abu_2")),
      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"
  )
) +
  plot_annotation(
    caption = paste0(
      "Source: Authors calculation based on SOGEDI database"
    )
  )
```

Figure 31: Correlation matrix of Abuse of social assistance by poor mothers



Reliability

```
mi_variable <- "wel_abu"
result2 <- alphas(db_proc, c("wel_abu_1","wel_abu_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.916503
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   2.000   3.500   3.546   5.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("wel_abu_1","wel_abu_2")], na.rm = TRUE
```

5.8.5 Paternalistic support for poor mothers

The items to measure this process are inspired by scales on teenage mothers but we adapted to capture attitudes towards the group of poor mothers based on our experience with similar scales (Kim et al., 2013). ##### **Descriptive analysis**

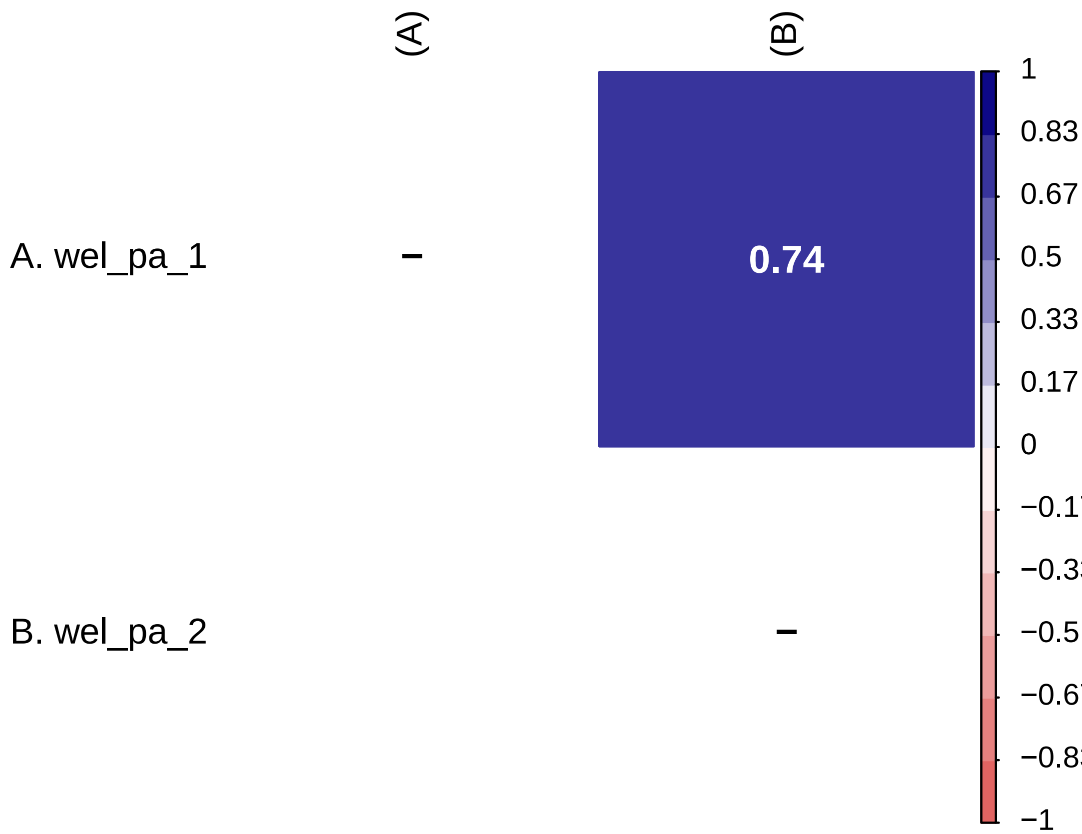
```
describe_kable(db_proc, c("wel_pa_1","wel_pa_2"))
```

Table 63: Descriptive statistics of Paternalistic support for poor mothers

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
wel_pa_1	1	4209	6.036	1.542	7	6.368	0	1	7	6	-1.718	2.265	0.024
wel_pa_2	2	4209	6.008	1.478	7	6.303	0	1	7	6	-1.617	2.081	0.023

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("wel_pa_1","wel_pa_2")),
      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"
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 32: Correlation matrix of Paternalistic support for poor mothers



Source: Authors calculation based on SOGEDI database

Reliability

```
mi_variable <- "wel_pa"
result2 <- alphas(db_proc, c("wel_pa_1","wel_pa_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8518911
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   5.500   7.000   6.022   7.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("wel_pa_1","wel_pa_2")], na.rm = TRUE)
```

5.8.6 Hostile support for poor mothers

The items to measure this process are inspired by scales on teenage mothers but we adapted to capture attitudes towards the group of poor mothers based on our experience with similar scales (Kim et al., 2013). ##### **Descriptive analysis**

```
describe_kable(db_proc, c("wel_ho_1","wel_ho_2"))
```

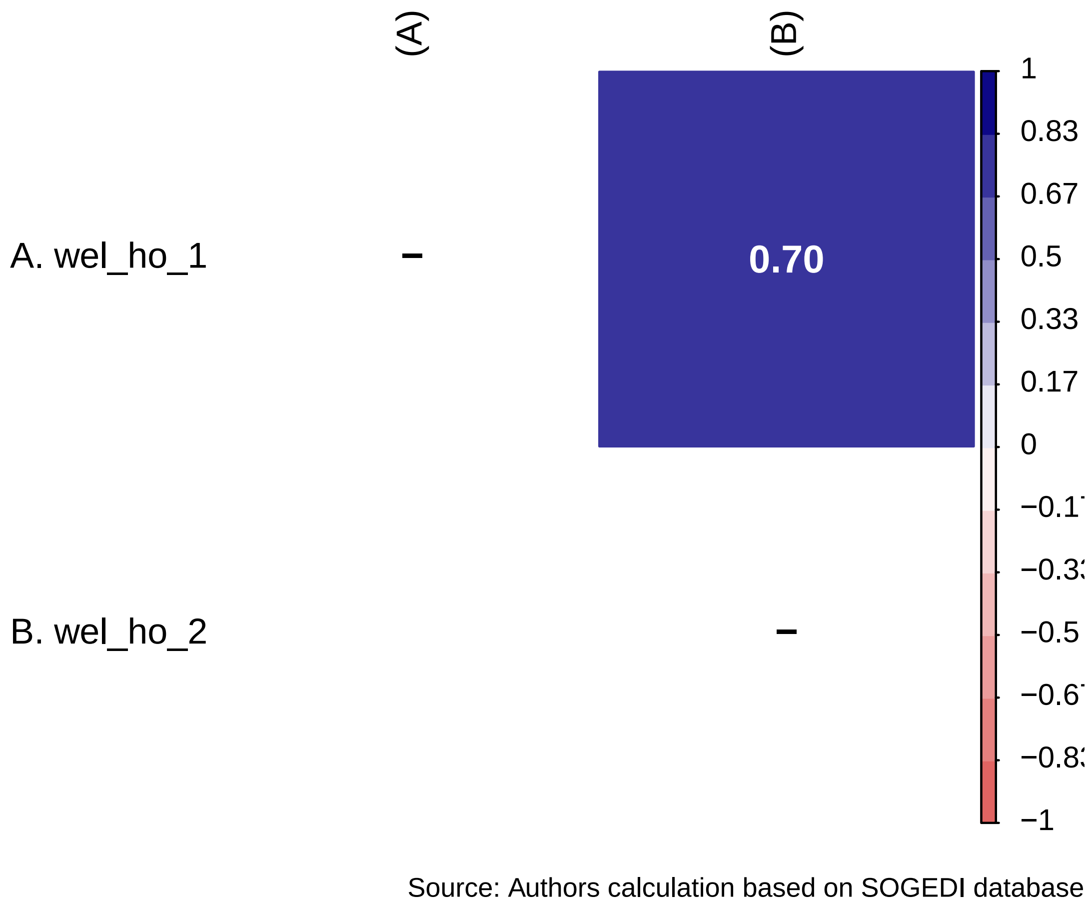
Table 64: Descriptive statistics of Hostile support for poor mothers

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
wel_ho_1	1	4209	3.730	2.312	4	3.663	4.448	1	7	6	0.139	-1.473	0.036
wel_ho_2	2	4209	4.434	2.249	5	4.542	2.965	1	7	6	-0.310	-1.335	0.035

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("wel_ho_1","wel_ho_2")),
      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"
    )
```

```
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 33: Correlation matrix of Hostile support for poor mothers



Reliability

```
mi_variable <- "wel_ho"
result2 <- alphas(db_proc, c("wel_ho_1","wel_ho_2"), mi_variable)
```

```r
result2$raw_alpha
```

```
[1] 0.825007
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   2.000   4.000   4.082   6.000   7.000
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("wel_ho_1","wel_ho_2")], na.rm = TRUE)
```

5.9 Block 9. Policies / Actions

5.9.1 Support for income redistribution

Items adapted from García-Sánchez et al. (2022).

Descriptive analysis

```r
describe_kable(db_proc, c("redi_1","redi_2"))
```

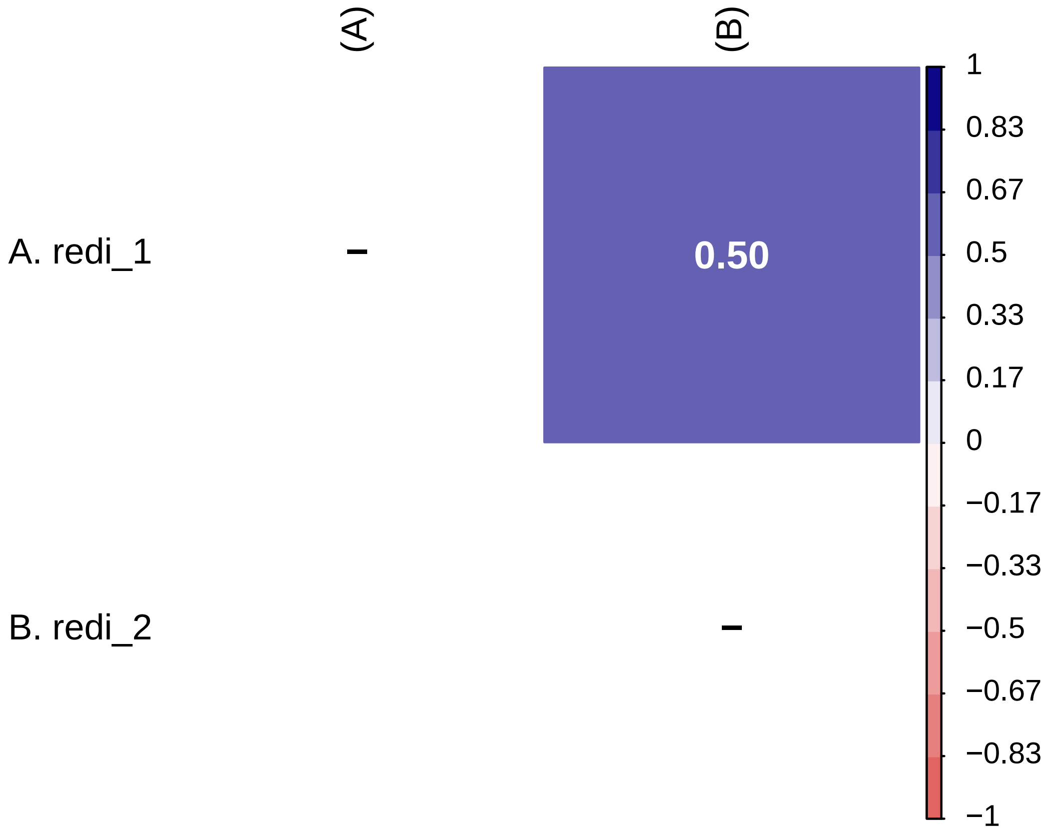
Table 65: Descriptive statistics of Support for income redistribution

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
redi_1	1	4209	4.795	1.984	5	4.993	2.965	1	7	6	-0.530	-0.834	0.031
redi_2	2	4209	4.937	2.041	5	5.170	2.965	1	7	6	-0.644	-0.820	0.031

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc,  c("redi_1","redi_2")),
      method = "color",
      type = "upper",
```

```r
    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"
  )
) +
  plot_annotation(
    caption = paste0(
      "Source: Authors calculation based on SOGEDI database"
    )
  )
```

Figure 34: Correlation matrix of Support for income redistribution



Source: Authors calculation based on SOGEDI database

Reliability

```
mi_variable <- "redi"
result2 <- alphas(db_proc,  c("redi_1","redi_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.6677836
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   4.000   5.000   4.866   6.500   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[,  c("redi_1","redi_2")], na.rm = TRUE)
```

5.9.2 Perception of effectiveness in the use of aids

Items previously used in Alcañiz-Colomer et al. (2023).

Descriptive analysis

```r
describe_kable(db_proc, c("effec_pw_1", "effec_pw_2", "effec_pm_1", "effec_pm_2"))
```

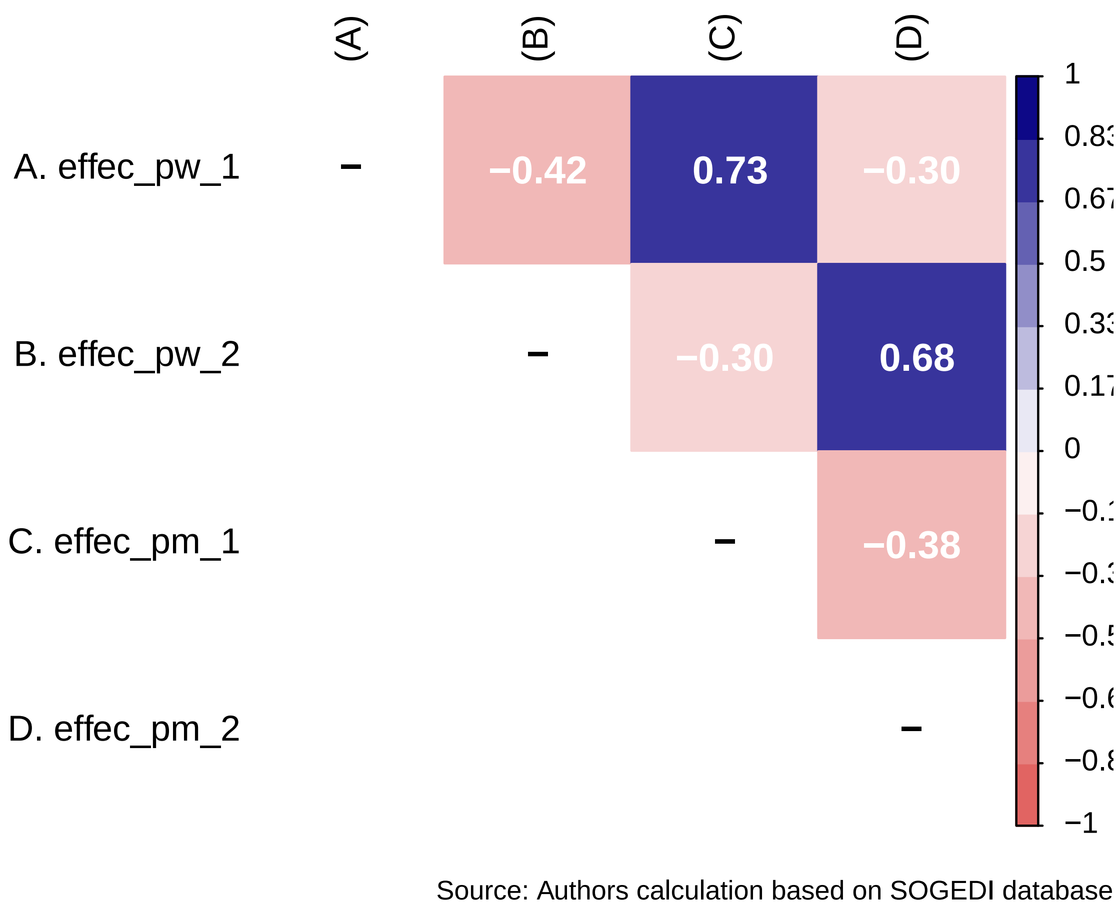
Table 66: Descriptive statistics of Perception of effectiveness in the use of aids

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
effec_pw_1	1	4209	3.852	1.796	4	3.824	1.483	1	7	6	-0.010	-0.865	0.028
effec_pw_2	2	4209	4.239	1.514	4	4.243	1.483	1	7	6	-0.026	-0.358	0.023
effec_pm_1	3	4209	4.334	1.735	4	4.397	1.483	1	7	6	-0.264	-0.718	0.027
effec_pm_2	4	4209	3.920	1.473	4	3.895	1.483	1	7	6	0.121	-0.234	0.023

```r
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("effec_pw_1", "effec_pw_2", "effec_pm_1", "effec_pm_
      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"
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 35: Correlation matrix of Perception of effectiveness in the use of aids



Reliability

```r
mi_variable <- "effec_pw"
result2 <- psych::alpha(db_proc[,c("effec_pw_1", "effec_pw_2")], check.keys = T)

result2$total$raw_alpha
```

```
[1] 0.5871212
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[,  c("effec_pw_1", "effec_pw_2")], na.rm =

summary(db_proc$effec_pw)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.500   4.000   4.046   4.500   7.000 
```

```r
mi_variable <- "effec_pm"
result2 <- psych::alpha(db_proc[,c("effec_pm_1", "effec_pm_2")], check.keys = T)

result2$total$raw_alpha
```

```
[1] 0.541424
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[,  c("effec_pm_1", "effec_pm_2")], na.rm =

summary(db_proc$effec_pw)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   3.500   4.000   4.046   4.500   7.000 
```

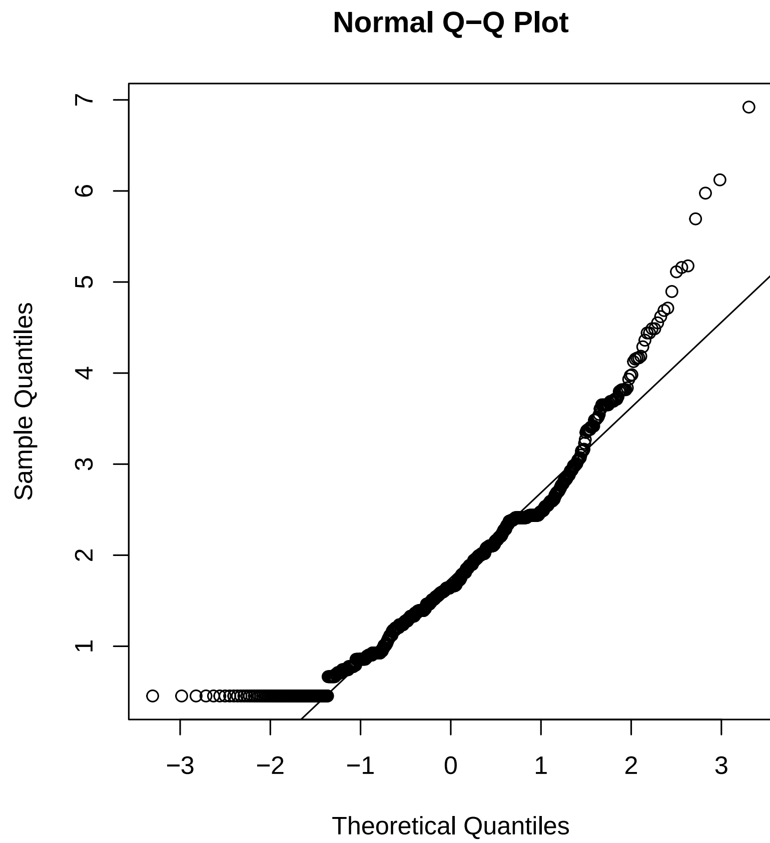
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality.

```r
mardia(db_pw[,c("effec_pw_1", "effec_pw_2", "effec_pm_1", "effec_pm_2")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_pw[, c("effec_pw_1", "effec_pw_2", "effec_pm_1", "effec_pm_2")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 1052 num.vars = 4 b1p = 2.79 skew = 490.05 with probability <= 0.0000000000000000000000000000000000000000000000000000000000000000000000000000000000000000
small sample skew = 492.01 with probability <= 0.00000000000000000000000000000000000000000000



b2p = 35.54 kurtosis = 27 with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```
# model
model_cfa <- '
  effectivness_pw =~ effec_pw_1 + effec_pw_2
  effectivness_pm =~ effec_pm_1 + effec_pm_2
   '
```

```r
# estimation
m18_cfa <- cfa(model = model_cfa,
               data = db_proc,
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m18_cfa_arg <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 1),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m18_cfa_cl <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 3),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m18_cfa_col <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 4),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m18_cfa_es <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 9),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m18_cfa_mex <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 13),
               estimator = "MLR",
               ordered = F,
               std.lv = F)
```

```r
cfa_tab_fit(
  models = list(m18_cfa, m18_cfa_cl, m18_cfa_mex),
  country_names = c("Overall scores", "Chile", "México")
```

```
)$fit_table
```

Table 67: Summary fit indices of Perception of effectiveness in the use of aids

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	2478.502 (1) ***	0.652	-1.090	0.767 [0.742-0.793]	0.154	59469.11
Chile	883	ML	479.246 (1) ***	0.622	-1.266	0.736 [0.681-0.792]	0.161	12516.65
México	846	ML	381.487 (1) ***	0.649	-1.105	0.671 [0.615-0.728]	0.158	12490.20

5.9.3 Social aids that promote autonomy vs. dependence

Single item based on Sainz et al. (2020) about governmental control of social welfare spending. This is supposed to capture dependence assistance towards poor men/women. Single item from the scale used in Alcañiz-Colomer et al. (2023). It is the item that worked best and most clearly represents dependence vs. autonomy.

Descriptive analysis

```
describe_kable(db_proc, c("depe_pw_1", "depe_pm_1", "aut_pw_1", "aut_pm_1"))
```

Table 68: Descriptive statistics of Social aids that promote autonomy vs. dependence

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
depe_pw_1	1	4209	4.544	1.880	5	4.680	1.483	1	7	6	-0.388	-0.811	0.029
depe_pm_1	2	4209	4.552	1.881	5	4.689	1.483	1	7	6	-0.387	-0.813	0.029
aut_pw_1	3	4209	3.920	1.819	4	3.900	1.483	1	7	6	0.005	-0.848	0.028
aut_pm_1	4	4209	3.751	1.813	4	3.692	1.483	1	7	6	0.097	-0.845	0.028

5.9.4 Progressive policies

Items comes from Jordan et al. (2021).

Descriptive analysis

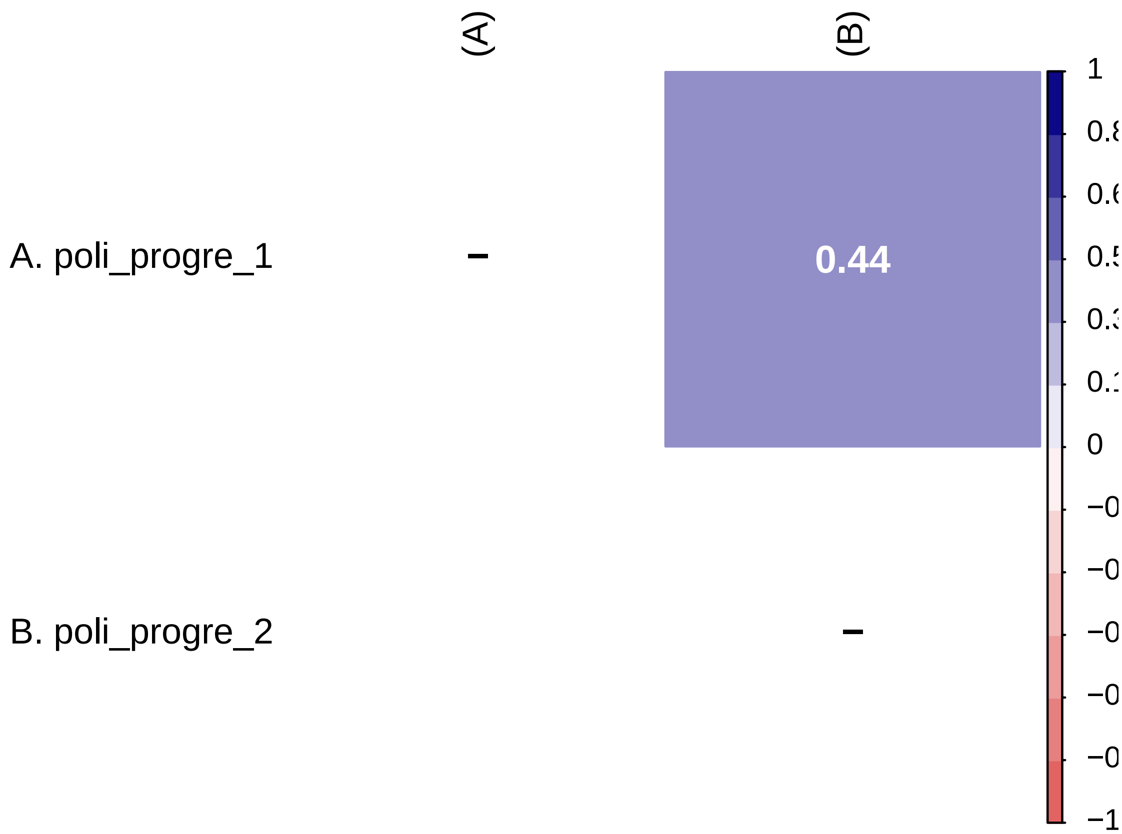
```
describe_kable(db_proc, c("poli_progre_1", "poli_progre_2"))
```

Table 69: Descriptive statistics of Progressive policies

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
poli_progre_1	1	4209	5.562	1.655	6	5.827	1.483	1	7	6	-1.051	0.352	0.026
poli_progre_2	2	4209	5.793	1.472	6	6.024	1.483	1	7	6	-1.180	0.842	0.023

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("poli_progre_1", "poli_progre_2")),
      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"
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 36: Correlation matrix of Progressive policies



Source: Authors calculation based on SOGEDI database

Reliability

```
mi_variable <- "poli_progre"
result2 <- alphas(db_proc,  c("poli_progre_1", "poli_progre_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.6076985
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   5.000   6.000   5.678   7.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[,  c("poli_progre_1", "poli_progre_2")], na
```

5.9.5 Restrictive policies

Items comes from Jordan et al. (2021).

Descriptive analysis

```
describe_kable(db_proc, c("poli_restri_1", "poli_restri_2"))
```

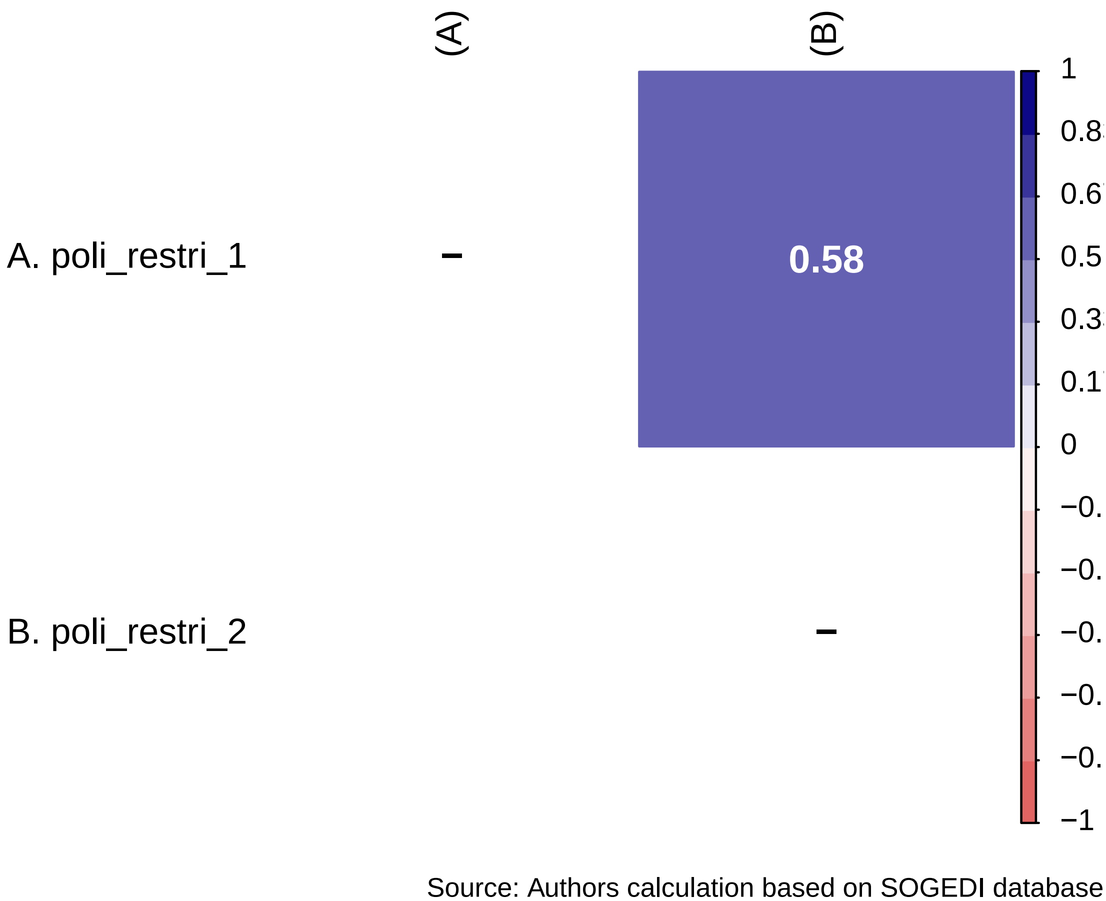
Table 70: Descriptive statistics of Restrictive policies

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
poli_restri_1	1	4209	4.906	2.102	5	5.132	2.965	1	7	6	-0.648	-0.896	0.032
poli_restri_2	2	4209	4.850	1.923	5	5.048	2.965	1	7	6	-0.551	-0.771	0.030

```
wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_proc, c("poli_restri_1", "poli_restri_2")),
      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"
```

```
    )
  ) +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

Figure 37: Correlation matrix of Restrictive policies



Reliability

```r
mi_variable <- "poli_restri"
result2 <- alphas(db_proc, c("poli_restri_1", "poli_restri_2"), mi_variable)

result2$raw_alpha
```

```
[1] 0.7332288
```

```r
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   4.000   5.000   4.878   6.500   7.000 
```

```r
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("poli_restri_1", "poli_restri_2")], na.
```

5.10 Block 10. Violence

5.10.1 Sexual harassment situations

We used items from previous publications (Cheek et al., 2023) but slightly modified them to adapt to the context of the study.

Descriptive analysis

```r
db_vio0 <- subset(db_proc, condi_viole == 0)
db_vio1 <- subset(db_proc, condi_viole == 1)


bind_rows(
  psych::describe(db_vio0[,c("hara_pw_1", "hara_pw_2", "hara_pw_3")]) %>%
    as_tibble() %>%
    mutate(target = "Poor Women")
  ,
  psych::describe(db_vio1[,c("hara_pw_1", "hara_pw_2", "hara_pw_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
) %>%
```

```r
  mutate(vars = paste0("hara_pw_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 71: Descriptive statistics of Sexual harassment situations

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Poor Women	hara_pw_1	2100	5.669	1.626	6	5.940	1.483	1	7	6	-1.109	0.346	0.035
	hara_pw_2	2100	6.420	1.146	7	6.713	0.000	1	7	6	-2.242	4.774	0.025
	hara_pw_3	2100	6.264	1.210	7	6.530	0.000	1	7	6	-1.756	2.618	0.026
Rich Women	hara_pw_1	2099	5.685	1.663	6	5.978	1.483	1	7	6	-1.190	0.548	0.036
	hara_pw_2	2099	6.365	1.190	7	6.658	0.000	1	7	6	-2.148	4.458	0.026
	hara_pw_3	2099	6.253	1.244	7	6.526	0.000	1	7	6	-1.821	2.934	0.027

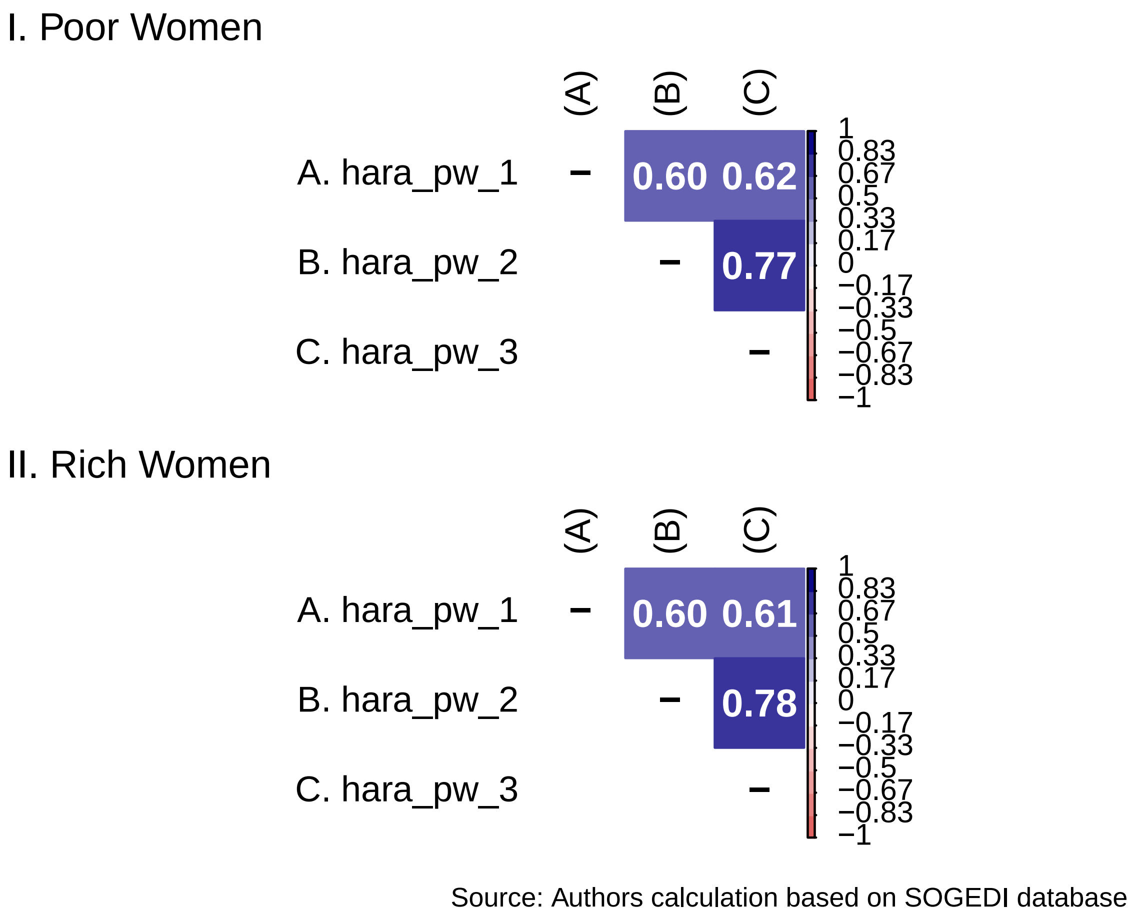
```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_vio0, c("hara_pw_1", "hara_pw_2", "hara_pw_3")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 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. Poor Women")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_vio1, c("hara_pw_1", "hara_pw_2", "hara_pw_3")),
      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. Rich Women")


p1/p2 +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 38: Correlation matrix of Sexual harassment situations



Reliability

```
mi_variable <- "hara"
result2 <- alphas(db_proc, c("hara_pw_1", "hara_pw_2", "hara_pw_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.8360801
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   5.667   6.667   6.109   7.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("hara_pw_1", "hara_pw_2", "hara_pw_3")]
```

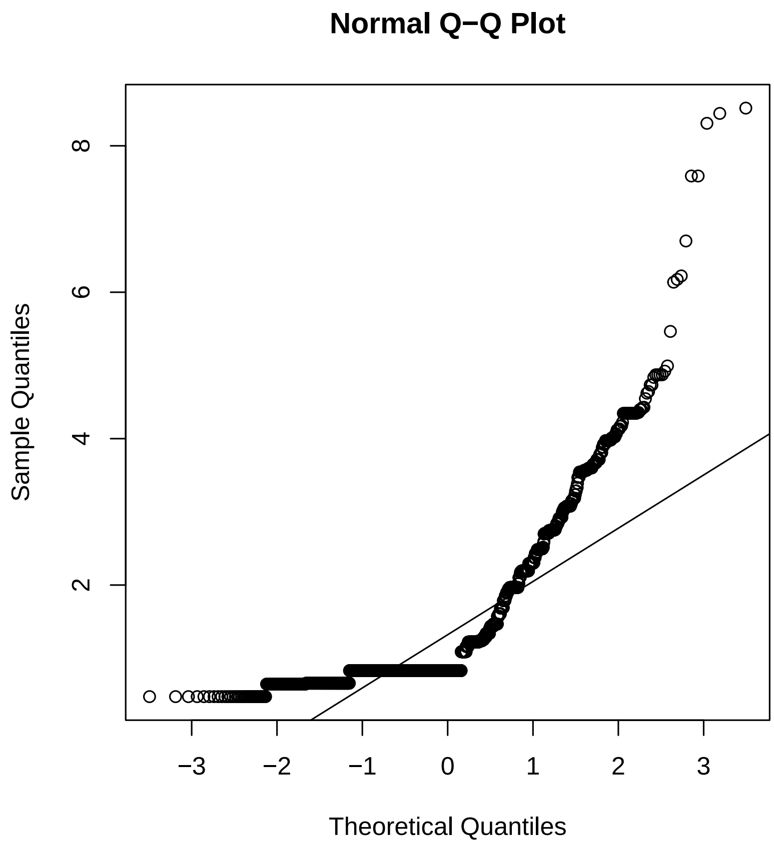
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality for each target.

```
mardia(db_vio0[,c("hara_pw_1", "hara_pw_2", "hara_pw_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_vio0[, c("hara_pw_1", "hara_pw_2", "hara_pw_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 2100 num.vars = 3 b1p = 10.55 skew = 3693.64 with probability <= 0 small sample skew = 3701.56 with probability <= 0 b2p = 37.7 kurtosis = 94.97 with

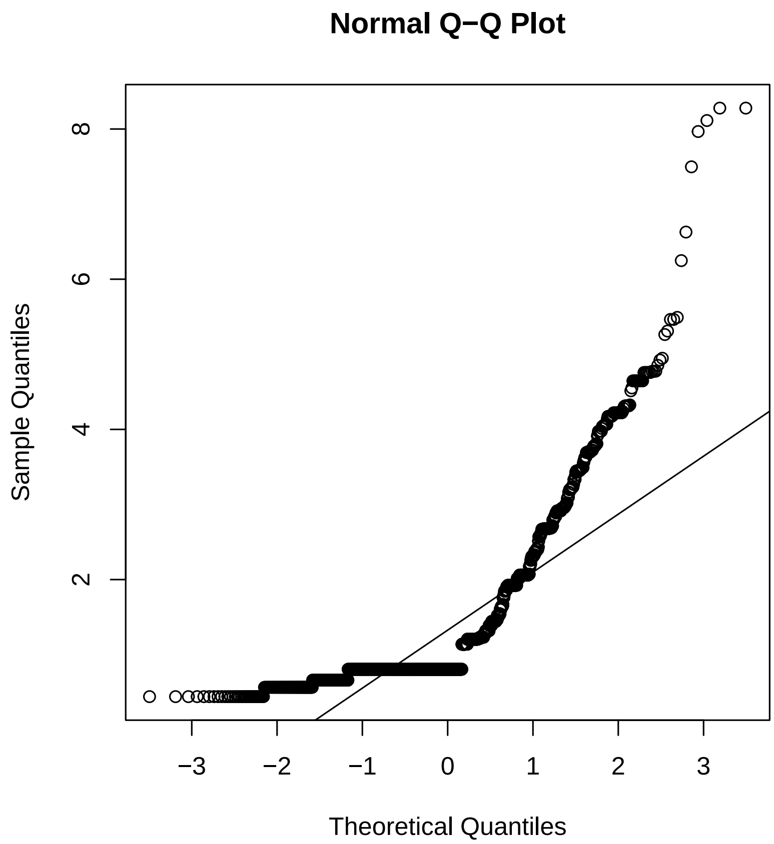


probability <= 0

```
mardia(db_vio1[,c("hara_pw_1", "hara_pw_2", "hara_pw_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_vio1[, c("hara_pw_1", "hara_pw_2", "hara_pw_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 2109 num.vars = 3 b1p = 10.3 skew = 3620.89 with probability <= 0 small sample skew = 3628.62 with probability <= 0 b2p = 38.49 kurtosis = 98.46 with



probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```
db_proc <- db_proc %>%
  mutate(target = if_else(condi_viole == 0, "Poor.Women", "Rich.Women"))

# model
model_cfa <- '
  harassment =~ hara_pw_1 + hara_pw_2 + hara_pw_3
   '

# estimation
# overall

m19_cfa_rw <- cfa(model = model_cfa,
```

```
              data = subset(db_proc, target == "Rich.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

m19_cfa_pw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)


# per country
db_proc$group <- interaction(db_proc$natio_recoded, db_proc$target)

# argentina

m19_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m19_cfa_pw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile

m19_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m19_cfa_pw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Women"),
                     estimator = "MLR",
```

```
                     ordered = F,
                     std.lv = F)

# colombia

m19_cfa_rw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m19_cfa_pw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# españa


m19_cfa_rw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m19_cfa_pw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# mexico

m19_cfa_rw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```
m19_cfa_pw_mex <- cfa(model = model_cfa,
                      data = subset(db_proc, group == "13.Poor.Women"),
                      estimator = "MLR",
                      ordered = F,
                      std.lv = F)
```

```
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m19_cfa_rw, m19_cfa_rw_arg, m19_cfa_rw_cl, m19_cfa_rw_col, m19_cfa_rw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
,
cfa_tab_fit(
  models = list(m19_cfa_pw, m19_cfa_pw_arg, m19_cfa_pw_cl, m19_cfa_pw_col, m19_cfa_pw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
```

```
  kableExtra::collapse_rows(columns = 1)
```

Table 72: Summary fit indices of Sexual harassment situations

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Women	2109	ML	0 (0)	1	1	0 [0-0]	0	18639.011
	Poor Women	2100	ML	0 (0)	1	1	0 [0-0]	0	18278.000
Argentina	Rich Women	427	ML	0 (0)	1	1	0 [0-0]	0	4000.984
	Poor Women	430	ML	0 (0)	1	1	0 [0-0]	0	3816.214
Chile	Rich Women	428	ML	0 (0)	1	1	0 [0-0]	0	3570.720
	Poor Women	432	ML	0 (0)	1	1	0 [0-0]	0	3665.025
Colombia	Rich Women	412	ML	0 (0)	1	1	0 [0-0]	0	3682.274
	Poor Women	412	ML	0 (0)	1	1	0 [0-0]	0	3937.165
Spain	Rich Women	417	ML	0 (0)	1	1	0 [0-0]	0	3646.568
	Poor Women	414	ML	0 (0)	1	1	0 [0-0]	0	3448.210
México	Rich Women	425	ML	0 (0)	1	1	0 [0-0]	0	3523.000
	Poor Women	412	ML	0 (0)	1	1	0 [0-0]	0	3088.497

5.10.2 Domestic abuse situations

We used items from previous publications (Cheek et al., 2023) but slightly modified them to adapt to the context of the study. ##### **Descriptive analysis**

```
bind_rows(
  psych::describe(db_vio0[,c("abu_pw_1", "abu_pw_2", "abu_pw_3")]) %>%
```

```r
    as_tibble() %>%
    mutate(target = "Poor Women")
  ,
  psych::describe(db_vio1[,c("abu_pw_1", "abu_pw_2", "abu_pw_3")]) %>%
    as_tibble() %>%
    mutate(target = "Rich Women")
) %>%
  mutate(vars = paste0("hara_pw_", vars)) %>%
  select(target, everything()) %>%
  group_by(target) %>%
  mutate(target = if_else(duplicated(target), NA, target)) %>%
  kableExtra::kable(format = "markdown", digits = 3)
```

Table 73: Descriptive statistics of Domestic abuse situations

target	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Poor Women	hara_pw_1	2100	6.449	1.126	7	6.737	0	1	7	6	-2.328	5.260	0.025
	hara_pw_2	2100	6.560	1.041	7	6.848	0	1	7	6	-2.722	7.461	0.023
	hara_pw_3	2100	6.664	0.941	7	6.940	0	1	7	6	-3.185	10.351	0.021
Rich Women	hara_pw_1	2109	6.501	1.038	7	6.764	0	1	7	6	-2.518	6.713	0.023
	hara_pw_2	2109	6.636	0.929	7	6.896	0	1	7	6	-3.096	10.384	0.020
	hara_pw_3	2109	6.743	0.827	7	6.978	0	1	7	6	-3.817	15.671	0.018

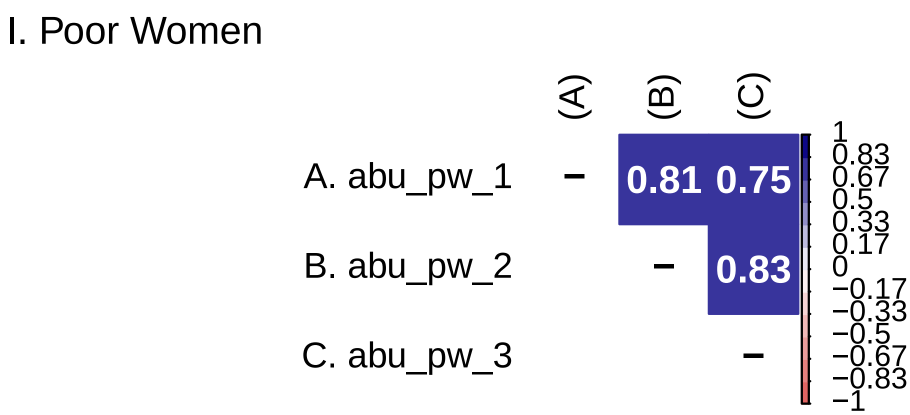
```r
p1 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_vio0, c("abu_pw_1", "abu_pw_2", "abu_pw_3")),
      method = "color",
      type = "upper",
      col = colorRampPalette(c("#E16462", "white", "#0D0887"))(12),
      tl.pos = "lt",
      tl.col = "black",
      addrect = 2,
      rect.col = "black",
```

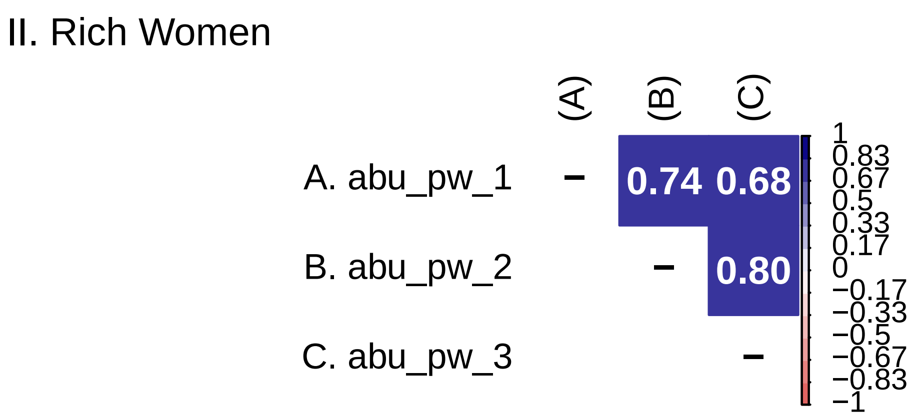
```
      addCoef.col = "white",
      cl.cex = 0.8,
      cl.align.text = 'l',
      number.cex = 1.1,
      na.label = "-",
      bg = "white"
    )
  ) + labs(title = "I. Poor Women")


p2 <- wrap_elements(
    ~corrplot::corrplot(
      fit_correlations(db_vio1, c("abu_pw_1", "abu_pw_2", "abu_pw_3")),
      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. Rich Women")


p1/p2 +
    plot_annotation(
      caption = paste0(
        "Source: Authors calculation based on SOGEDI database"
      )
    )
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

```
Error in graphics::par(old_gp) :
  invalid value specified for graphical parameter "pin"
```

Figure 39: Correlation matrix of Domestic abuse situations





Source: Authors calculation based on SOGEDI database

Reliability

```r
mi_variable <- "abu"
result2 <- alphas(db_proc, c("abu_pw_1", "abu_pw_2", "abu_pw_3"), mi_variable)

result2$raw_alpha
```

```
[1] 0.9074704
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   6.667   7.000   6.592   7.000   7.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("abu_pw_1", "abu_pw_2", "abu_pw_3")], n
```

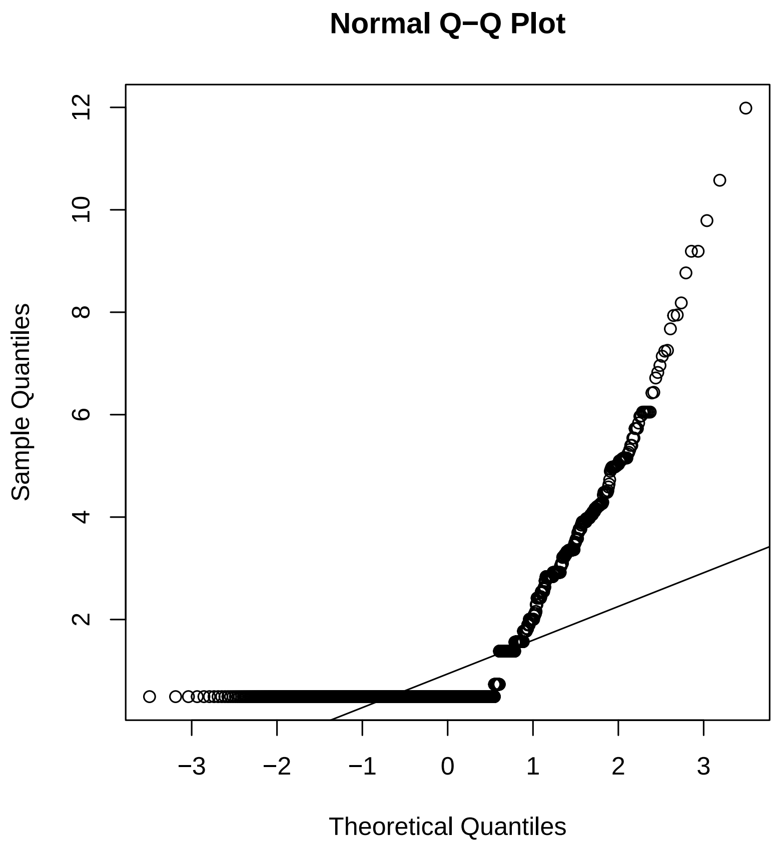
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality for each target.

```
mardia(db_vio0[,c("abu_pw_1", "abu_pw_2", "abu_pw_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_vio0[, c("abu_pw_1", "abu_pw_2", "abu_pw_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 2100 num.vars = 3 b1p = 26.1 skew = 9135.94 with probability <= 0 small sample skew = 9155.53 with probability <= 0 b2p = 80.82 kurtosis = 275.33 with

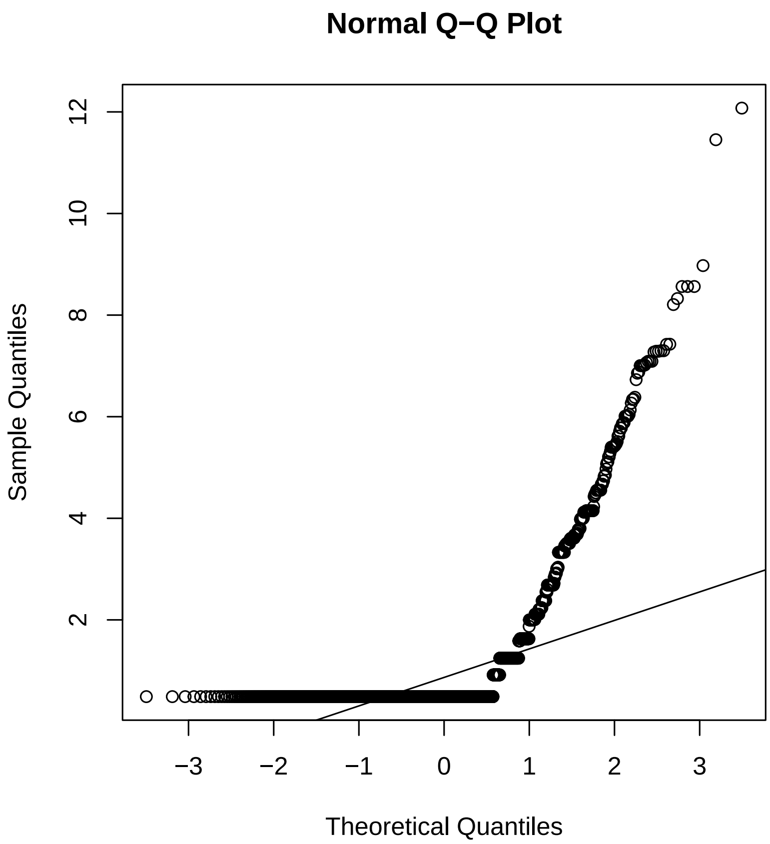


probability <= 0

```
mardia(db_vio1[,c("abu_pw_1", "abu_pw_2", "abu_pw_3")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_vio1[, c("abu_pw_1", "abu_pw_2", "abu_pw_3")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 2109 num.vars = 3 b1p = 34.23 skew = 12030.6 with probability <= 0 small sample skew = 12056.28 with probability <= 0 b2p = 90.31 kurtosis = 315.7 with



probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```
# model
model_cfa <- '
  abuse =~ abu_pw_1 + abu_pw_2 + abu_pw_3
   '

# estimation
# overall

m20_cfa_rw <- cfa(model = model_cfa,
                 data = subset(db_proc, target == "Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
```

```r
              std.lv = F)

m20_cfa_pw <- cfa(model = model_cfa,
              data = subset(db_proc, target == "Poor.Women"),
              estimator = "MLR",
              ordered = F,
              std.lv = F)

# argentina

m20_cfa_rw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Rich.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

m20_cfa_pw_arg <- cfa(model = model_cfa,
                 data = subset(db_proc, group == "1.Poor.Women"),
                 estimator = "MLR",
                 ordered = F,
                 std.lv = F)

# chile

m20_cfa_rw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m20_cfa_pw_cl <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "3.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# colombia

m20_cfa_rw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Rich.Women"),
```

```r
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m20_cfa_pw_col <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "4.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# españa


m20_cfa_rw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m20_cfa_pw_esp <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "9.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

# mexico

m20_cfa_rw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Rich.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)

m20_cfa_pw_mex <- cfa(model = model_cfa,
                     data = subset(db_proc, group == "13.Poor.Women"),
                     estimator = "MLR",
                     ordered = F,
                     std.lv = F)
```

```
colnames_fit  <- c("","Target","$N$","Estimator","$\\chi^2$ (df)","CFI","TLI","RMSEA 9


bind_rows(
cfa_tab_fit(
  models = list(m20_cfa_rw, m20_cfa_rw_arg, m20_cfa_rw_cl, m20_cfa_rw_col, m20_cfa_rw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Rich Women")
,
cfa_tab_fit(
  models = list(m20_cfa_pw, m20_cfa_pw_arg, m20_cfa_pw_cl, m20_cfa_pw_col, m20_cfa_pw_
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
)$sum_fit %>%
  mutate(target = "Poor Women")
) %>%
  select(country, target, everything()) %>%
  mutate(country = factor(country, levels = c("Overall scores", "Argentina", "Chile",
  group_by(country) %>%
  arrange(country) %>%
  mutate(country = if_else(duplicated(country), NA, country)) %>%
  kableExtra::kable(
  format     = "markdown",
  digits     = 3,
  booktabs   = TRUE,
  col.names  = colnames_fit,
  caption    = NULL
) %>%
  kableExtra::kable_styling(
    full_width        = TRUE,
    font_size         = 11,
    latex_options     = "HOLD_position",
    bootstrap_options = c("striped", "bordered")
  ) %>%
  kableExtra::collapse_rows(columns = 1)
```

Table 74: Summary fit indices of Domestic abuse situations

	Target	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	Rich Women	2109	ML	0 (0)	1	1	0 [0-0]	0	13016.345
	Poor Women	2100	ML	0 (0)	1	1	0 [0-0]	0	13440.990
Argentina	Rich Women	427	ML	0 (0)	1	1	0 [0-0]	0	2467.874
	Poor Women	430	ML	0 (0)	1	1	0 [0-0]	0	2687.205
Chile	Rich Women	428	ML	0 (0)	1	1	0 [0-0]	0	2638.312
	Poor Women	432	ML	0 (0)	1	1	0 [0-0]	0	2840.373
Colombia	Rich Women	412	ML	0 (0)	1	1	0 [0-0]	0	2790.489
	Poor Women	412	ML	0 (0)	1	1	0 [0-0]	0	2997.369
Spain	Rich Women	417	ML	0 (0)	1	1	0 [0-0]	0	1998.865
	Poor Women	414	ML	0 (0)	1	1	0 [0-0]	0	1841.201
México	Rich Women	425	ML	0 (0)	1	1	0 [0-0]	0	2783.450
	Poor Women	412	ML	0 (0)	1	1	0 [0-0]	0	2652.700

5.10.3 Type of violence

We have created these items with the purpose of determining if there are differences in the type of violence perceived associated with each social class. ##### **Descriptive analysis**

```
describe_kable(db_proc, c("viole_pw_1", "viole_pw_2", "viole_pw_3", "viole_pw_4", "vio
```

Table 75: Descriptive statistics of Type of violence items

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
viole_pw_1	1	4209	5.499	1.530	6	5.705	1.483	1	7	6	-0.830	-0.017	0.024
viole_pw_2	2	4209	5.707	1.437	6	5.910	1.483	1	7	6	-1.024	0.484	0.022
viole_pw_3	3	4209	5.707	1.462	6	5.926	1.483	1	7	6	-1.082	0.583	0.023
viole_pw_4	4	4209	5.425	1.594	6	5.632	1.483	1	7	6	-0.797	-0.184	0.025
viole_pw_5	5	4209	5.363	1.741	6	5.616	1.483	1	7	6	-0.892	-0.154	0.027
viole_pw_6	6	4209	5.445	1.606	6	5.668	1.483	1	7	6	-0.882	0.027	0.025

5.10.4 Barriers to leaving an abusive relationship

We have created these items with the purpose of determining if there are differences in the type of barriers associated with leaving an abusive relationship each social class. ##### **Descriptive analysis**

```
describe_kable(db_proc, c("barri_pw_1", "barri_pw_2", "barri_pw_3", "barri_pw_4", "bar
```

Table 76: Descriptive statistics of Barriers to leaving an abusive relationship items

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
barri_pw_1	1	4209	5.552	1.534	6	5.776	1.483	1	7	6	-0.944	0.202	0.024
barri_pw_2	2	4209	5.402	1.767	6	5.680	1.483	1	7	6	-0.968	-0.073	0.027
barri_pw_3	3	4209	5.249	1.624	5	5.428	1.483	1	7	6	-0.683	-0.304	0.025
barri_pw_4	4	4209	5.012	1.819	5	5.207	1.483	1	7	6	-0.612	-0.645	0.028
barri_pw_5	5	4209	5.530	1.482	6	5.723	1.483	1	7	6	-0.895	0.255	0.023

5.10.5 Perpetration of violence

Exploratory items from Rosa Rodríguez Bailón.

Descriptive analysis

```
describe_kable(db_proc, c("perpe_1", "perpe_2", "perpe_3", "perpe_4", "perpe_5"))
```

Table 77: Descriptive statistics of Perpetration of violence

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
perpe_1	1	4209	1.158	0.572	1	1.000	0	1	5	4	4.171	18.588	0.009
perpe_2	2	4209	1.383	0.762	1	1.194	0	1	5	4	2.282	5.410	0.012
perpe_3	3	4209	1.135	0.546	1	1.000	0	1	5	4	4.670	23.259	0.008
perpe_4	4	4209	1.465	0.800	1	1.288	0	1	5	4	1.866	3.372	0.012
perpe_5	5	4209	1.119	0.519	1	1.000	0	1	5	4	5.098	27.932	0.008

Reliability

```
mi_variable <- "perpe"
result2 <- alphas(db_proc, c("perpe_1", "perpe_2", "perpe_3", "perpe_4", "perpe_5"), m

result2$raw_alpha
```

```
[1] 0.8855049
```

```
result2$new_var_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.000   1.000   1.252   1.200   5.000 
```

```
db_proc[[mi_variable]] <- rowMeans(db_proc[, c("perpe_1", "perpe_2", "perpe_3", "perpe
```

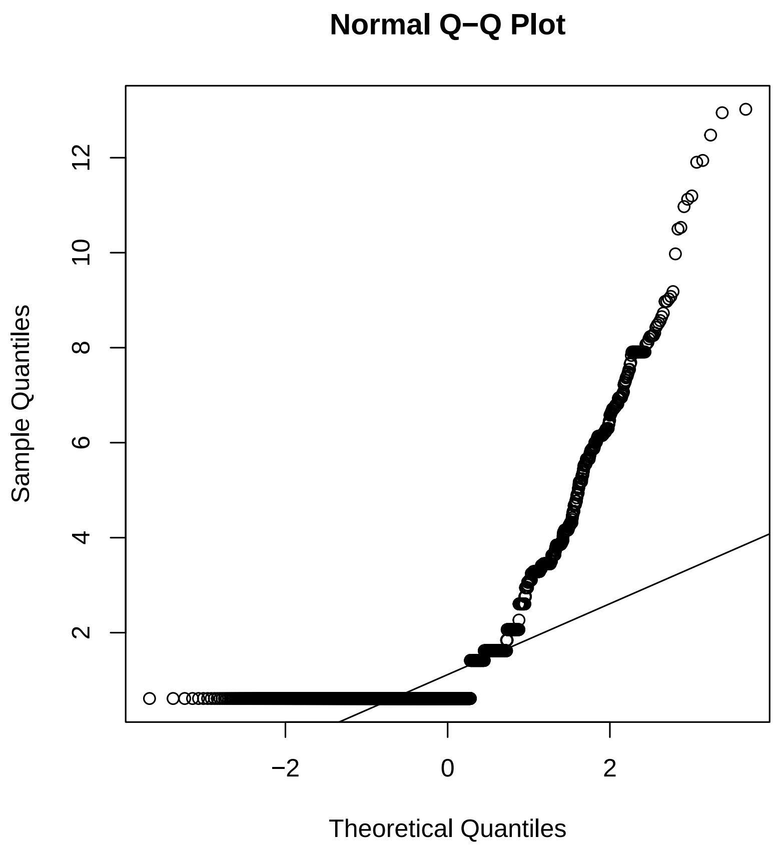
Confirmatory factor analysis

Mardia's test for evaluate multivariate normality.

```r
mardia(db_proc[,c("perpe_1", "perpe_2", "perpe_3", "perpe_4", "perpe_5")],
       na.rm = T, plot=T)
```

Call: mardia(x = db_proc[, c("perpe_1", "perpe_2", "perpe_3", "perpe_4", "perpe_5")], na.rm = T, plot = T)

Mardia tests of multivariate skew and kurtosis Use describe(x) the to get univariate tests n.obs = 4209 num.vars = 5 b1p = 61.96 skew = 43465.5 with probability <= 0 small sample skew = 43506.82 with probability <= 0 b2p = 176.96 kurtosis = 550.38



with probability <= 0

We first specify the factorial structure of the items, then fit models using a robust maximum likelihood estimator for the entire sample as well as for each country individually. The goodness of fit indicators are shown.

```r
# model
model_cfa <- ' perpe_viole =~ perpe_1 + perpe_2 + perpe_3 + perpe_4 + perpe_5 '
```

```r
# estimation
m21_cfa <- cfa(model = model_cfa,
               data = db_proc,
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m21_cfa_arg <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 1),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m21_cfa_cl <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 3),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m21_cfa_col <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 4),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m21_cfa_es <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 9),
               estimator = "MLR",
               ordered = F,
               std.lv = F)

m21_cfa_mex <- cfa(model = model_cfa,
               data = subset(db_proc, country_residence_recoded == 13),
               estimator = "MLR",
               ordered = F,
               std.lv = F)
```

```r
cfa_tab_fit(
  models = list(m21_cfa, m21_cfa_arg, m21_cfa_cl, m21_cfa_col, m21_cfa_es, m21_cfa_mex
  country_names = c("Overall scores", "Argentina", "Chile", "Colombia", "Spain", "Méxi
```

```
)$fit_table
```

Table 78: Summary fit indices of Perpetration of violence

	N	Estimator	χ^2 (df)	CFI	TLI	RMSEA 90% CI [Lower-Upper]	SRMR	AIC
Overall scores	4209	ML	1268.801 (5) ***	0.908	0.816	0.245 [0.234-0.256]	0.065	27755.146
Argentina	807	ML	355.444 (5) ***	0.854	0.708	0.295 [0.269-0.321]	0.094	4731.560
Chile	883	ML	263.913 (5) ***	0.901	0.802	0.242 [0.218-0.267]	0.067	5557.754
Colombia	833	ML	242.026 (5) ***	0.920	0.840	0.239 [0.213-0.265]	0.056	5916.789
Spain	835	ML	302.777 (5) ***	0.899	0.797	0.267 [0.242-0.293]	0.082	3335.810
México	846	ML	227.252 (5) ***	0.925	0.849	0.229 [0.204-0.255]	0.049	6964.814

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