The Personality Structures of the 50 States

Anisha Babu, Diana DeWald, Ian Shryock, Dillon Welindt, Futing Zou

Contents


```
SAPA <- SAPA %>%
  # filter in US
  filter(country == "USA") %>%
  # filter 50 states
  filter(!state %in% c('District of Columbia', 'Guam', 'Palau','Puerto Rico', 'Virgin Islands',
                       'Northern Mariana Islands', 'American Samoa', 'Marshall Islands', NA))

# filter out rows with all NA
SAPA <- SAPA[rowSums(is.na(SAPA)) < 99, ]

# in list form select only used Q's
usedQ <- colnames(SAPA[8:106])
IPIPkeys <- map(IPIPkeysList, function(x) {
    x[match(usedQ, x)]
    na.omit(x)
})
# select only IPIP 100
IPIPkeys <- IPIPkeys[1:4]
```

```r
# idk if this is what we want here - tableby package not available
map((SAPA[c(2,3,5,6,7)]), table)
```

```
## $gender
##
## Female   Male
##  56901  24465
##
## $age
##
##   14   15   16   17   18   19   20   21   22   23   24   25   26   27   28   29
##  767 1113 3129 6462 7707 6709 5896 4885 3621 2999 2569 2300 2193 2085 1887 1649
##   30   31   32   33   34   35   36   37   38   39   40   41   42   43   44   45
## 1590 1453 1345 1230 1212 1240 1152 1159 1069  958 1010  840  866  847  815  791
##   46   47   48   49   50   51   52   53   54   55   56   57   58   59   60   61
##  688  691  681  626  665  542  537  500  433  389  309  301  246  217  212  126
##   62   63   64   65   66   67   68   69   70   71   72   73   74   75   76   77
##  132   88   68   82   50   47   29   27   27   22   21    6   12    7    5    4
##   78   79   80   81   82   83   84   85   86   87   88   89   90
##    5    3    4    1    1    2    1    3    2    2    1    2    1
##
## $state
##
##        Alabama         Alaska        Arizona       Arkansas     California
##            643            555            866            577           9709
##       Colorado    Connecticut       Delaware        Florida        Georgia
##           1097            986            592           2936           2414
##         Hawaii          Idaho       Illinois        Indiana           Iowa
##            292            340           5520           1707            982
##         Kansas       Kentucky      Louisiana          Maine       Maryland
##            808            820           2030            356           1772
##  Massachusetts       Michigan      Minnesota    Mississippi       Missouri
##           1935           2549           2104            604           1611
##        Montana       Nebraska         Nevada  New Hampshire     New Jersey
##            243            580            274            389           2495
##     New Mexico       New York North Carolina   North Dakota           Ohio
##           1199           4942           1454            190           3600
##       Oklahoma         Oregon   Pennsylvania   Rhode Island South Carolina
##            771           1203           4758            422           1010
##   South Dakota      Tennessee          Texas           Utah        Vermont
##            172           1133           4662            487            161
##       Virginia     Washington  West Virginia      Wisconsin        Wyoming
##           2787           1742            384           2377            126
##
## $race
##
## African American          Chinese Indian/Pakistani         Japanese
##             6108             1129              469              257
##           Korean           Latino          Mexican  Native American
##              500             2079             2166              728
##            Other      Other Asian Pacific Islander        Philipino
##             3067              566              305              615
##     Puerto Rican  White/Caucasian
```

```
##              512            62859
##
## $education
##
##                 College graduate     Currently attending college
##                            12381                          32469
## Graduate or professional degree            High school graduate
##                            10338                           6145
##              Less than 12 years   Some college did not graduate
##                            11759                           8274
```

```
# score items
scores <- psych::scoreItems(keys = IPIPkeys, items = SAPA, min=1, max=6, totals = FALSE, impute = 'none
```

```
library(arsenal)

# demographic table
demog_tab <- summary(tableby(~ age + gender + race + education,
                             data = SAPA, test = FALSE),
                     title = "Full Sample Demographics")
demog_tab
```

Table 1: (#tab:#3 descriptives statistics)Full Sample Demographics

	Overall (N=81366)
age	
Mean (SD)	27.177 (11.343)
Range	14.000 - 90.000
gender	
Female	56901 (69.9%)
Male	24465 (30.1%)
race	
N-Miss	6
African American	6108 (7.5%)
Chinese	1129 (1.4%)
Indian/Pakistani	469 (0.6%)
Japanese	257 (0.3%)
Korean	500 (0.6%)
Latino	2079 (2.6%)
Mexican	2166 (2.7%)
Native American	728 (0.9%)
Other	3067 (3.8%)
Other Asian	566 (0.7%)
Pacific Islander	305 (0.4%)
Philipino	615 (0.8%)
Puerto Rican	512 (0.6%)
White/Caucasian	62859 (77.3%)
education	
College graduate	12381 (15.2%)
Currently attending college	32469 (39.9%)
Graduate or professional degree	10338 (12.7%)

	Overall (N=81366)
High school graduate	6145 (7.6%)
Less than 12 years	11759 (14.5%)
Some college did not graduate	8274 (10.2%)

```
# to add for final: demographic table grouped by state

# to add for final:  improve correlation matrix format/names (below), include other personality traits


res <- cor(scores, use = "complete.obs")
round(res, 2)
```

```
                      IPIP100agreeableness IPIP100conscientiousness
```

IPIP100agreeableness 1.00 0.21 IPIP100conscientiousness 0.21 1.00 IPIP100extraversion 0.38 0.13 IPIP100intellect 0.16 0.08 IPIP100extraversion IPIP100intellect IPIP100agreeableness 0.38 0.16 IPIP100conscientiousness 0.13 0.08 IPIP100extraversion 1.00 0.22 IPIP100intellect 0.22 1.00

```
library(apaTables)

apa.cor.table(scores, filename="Corr_table.doc", show.conf.interval=F)
```

The ability to suppress reporting of reporting confidence intervals has been deprecated in this version. The function argument show.conf.interval will be removed in a later version.

Means, standard deviations, and correlations with confidence intervals

Variable M SD 1 2 3
1. IPIP100agreeableness 4.67 0.77

2. IPIP100conscientiousness 4.14 0.92 .21**
   [.21, .22]
3. IPIP100extraversion 3.92 1.02 .38** .13**
   [.37, .38] [.13, .14]
4. IPIP100intellect 4.59 0.73 .16** .08** .22**
   [.15, .16] [.07, .08] [.21, .23]

Note. M and SD are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates p $<$ .05. ** indicates p $<$ .01.

```
# average scores on included survey questions
average_surveyscores <- SAPA %>%
  summarize_at(vars(q_76:q_1989), mean, na.rm = TRUE)


# average scores on survey questions by state (for final: can group by other variables as well)
average_statescores <- SAPA %>%
  group_by(state) %>%
  summarize_at(vars(q_76:q_1989), mean, na.rm = TRUE)
```

```r
# combine demographics & traits
factorSAPA <- cbind(SAPA[1:7], scores)

# nest data by state
by_state <- split(factorSAPA, factorSAPA$state)

# descriptive stats - THERE SHOULD BE A BETTER WAY TO DO THIS (SOME KIND OF NESTED MAP FXN?)  ## summar
stateAgree <- map(by_state, ~summarize(.x, meanFactor = mean(IPIP100agreeableness, na.rm = TRUE),
                                       sdFactor = sd(IPIP100agreeableness, na.rm = TRUE),
                                       nFactor = length(IPIP100agreeableness)))
stateCons <- map(by_state, ~summarize(.x, meanFactor = mean(IPIP100conscientiousness, na.rm = TRUE),
                                       sdFactor = sd(IPIP100conscientiousness, na.rm = TRUE),
                                       nFactor = length(IPIP100conscientiousness)))
stateExtra <- map(by_state, ~summarize(.x, meanFactor = mean(IPIP100extraversion, na.rm = TRUE),
                                       sdFactor = sd(IPIP100extraversion, na.rm = TRUE),
                                       nFactor = length(IPIP100extraversion)))
stateIntel <- map(by_state, ~summarize(.x, meanFactor = mean(IPIP100intellect, na.rm = TRUE),
                                       sdFactor = sd(IPIP100intellect, na.rm = TRUE),
                                       nFactor = length(IPIP100intellect)))
# group all factors in list
allFactor = list(stateAgree, stateCons, stateExtra, stateIntel)
names(allFactor) = c('Agreeableness', 'Conscientiousness', 'Extraversion', 'Intellect')

# function to create table - SHOULD FIND A WAY TO CAPTION EACH TABLE BY STATE & FACTOR
makeTable <- function(x) {
  kable(x, booktabs = TRUE, longtable = TRUE, col.names = c("Mean", "SD", "N"),
        caption = paste('State of ', x, ' Descriptives')) %>%
    landscape() %>%
    kable_styling(font_size = 12, latex_options = c("scale_down", "repeat_header")) %>%
    kable_classic()
}

# create tables for each factor & state
map(allFactor, ~map(.x, ~makeTable(.x)))
```

```r
stateFactordf
```

```
##   Alabama Alaska Arizona Arkansas California Colorado Connecticut Delaware
## 1       5      6       5        5          5        5           5        6
##   Florida Georgia Hawaii Idaho Illinois Indiana Iowa Kansas Kentucky Louisiana
## 1       5       5      6     6        5       5    5      5        5         5
##   Maine Maryland Massachusetts Michigan Minnesota Mississippi Missouri Montana
## 1     5        5             5        5         5           6        5       7
##   Nebraska Nevada New.Hampshire New.Jersey New.Mexico New.York North.Carolina
## 1        5      7             6          5          5        5              5
##   North.Dakota Ohio Oklahoma Oregon Pennsylvania Rhode.Island South.Carolina
## 1            7    5        5      5            5            7              5
##   South.Dakota Tennessee Texas Utah Vermont Virginia Washington West.Virginia
## 1            7         5     5    5       8        5          5             6
##   Wisconsin Wyoming
## 1         5       7
```

1 Introduction

1.1 Big Five

One of the most widely replicated findings within the field of personality psychology is the Big Five structure of personality. With roots in the 1800's, personality psychology sought to determine the best way to represent the large number of personality traits in a concise structure. This research initially involved researchers providing participants with large numbers of trait descriptive adjectives and asking them to rate the extent to which those adjectives characterize themselves or someone they knew. Dimension reduction analyses were then used to create a simpler structure from those responses.

Multiple research groups began converging on the five factor structure as early as the 1960's, with an increasing consensus by the late 1980's. Most of the recent work on the big five has been conducted through a combination of confirmatory factor analysis and theory driven selection of survey items based on previous findings about the structure.

1.2 Geographical Personality

In recent years, there has been increasing focus on regional variation of personality traits within the United States. Work has examined the extent to which regions of the US differ on the Big Five domains and can be said to have distinct and characteristic combinations of trait levels. For example, Rentfrow and colleagues (2013) show that the south and midwest are best characterized as friendly and conventional, whereas the west is relaxed and creative, and the northeast is temperamental and uninhibited.

A limitation of this work is that it examines the extent to which the five factor structure captures each region and what differences in the levels of each factor are due to regional variation. This research utilizes confirmatory factor analyses that assume that the five factor structure is the ideal level of dimensionality to characterize all regions.

1.3 Cross Cultural Studies

Much of the cross-cultural work on personality structure has found some support for the notion that the five factor structure has applicability in a number of cultures. However, these studies typically are conducted from an etic perspective that translate the items used in western samples.

However, when studies are conducted from an emic perspective – that is, using trait descriptive adjectives from the language of the culture, rather than translations of items used in the big five framework – different structures emerge. A varying number of factors have been found to best fit different cultures, ranging from one to seven in many cases.

1.4 Geographical Factor Structure within US

Within the US, the regional variation in factor structures has not been an extensively studied topic. Because most research operates within a framework that utilizes confirmatory factor analysis, there is little information on the extent to which regions differ in their factor structure.

In the current study, we use exploratory factor analyses to provide estimates of the optimal factor structures for each of the fifty states.

2 Brief Methods

2.1 Measures

The International Personality Item Pool is an open-source repository of personality trait items that have been researched extensively in the big five tradition. The current study uses ninety nine of one hundred items from the IPIP-100. Participants rated themselves on a number of personality traits from 1- not at all like me to 6- very much like me.

2.2 Data Collection

Data were obtained from the Harvard Dataverse. Data were initially collected using the Synthetic Aperture for Personality Assessment (Revelle et al., 2016; Condon and Revelle, 2014; Wilt et al., 2011) which utilizes a massively missing completely at random design, wherein each participant only provides responses to a fraction of items.

3 Analyses

First, we provide descriptive norms for the entire US sample, and then by state.

Next, we use parallel analysis to determine the optimal number of factors in the whole sample. Our hypothesis is that five factors will provide an optimal fit.

The main analyses are fifty parallel analyses, one for every state, that estimates the optimal number of personality dimensions for each state. We hypothesize that there will be variation in the number of ideal dimensions across states.

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