Personality, Ability and Interests: Real World Outcomes

Presented as part of a symposium: Broadening the scope of personality research: The place of Personality, Ability, and Interests in Determining Real World Outcomes

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Slides at http://personality-project.org/sapa.html

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Outline

Integrating Abilities interest in a broad theory of personality

1. Since about 1950, American personality research has tended to deemphasize (indeed, ignore) cognitive and motivational aspects of personality.
   - Researchers talk about child development and clinical diagnoses as if these were unrelated to each other and to the field of personality.
   - It is thought that young children have temperament, college students personality, clinical patients have psychopatholgy, and these should be studied as separate areas of research.
2. European research, on the other hand, by keeping the term "Individual Differences" alive, has continued to study these important aspects of individuality.
3. We attempt to continue this tradition.

Breadth vs. depth of measurement

1. Factor structure of domains needs multiple constructs to define structure.
2. Each construct needs multiple items to measure reliably.
3. This leads to an explosion of potential items .
4. But, people are willing to only answer a limited number of items.
5. This leads to the use of short and shorter forms (the NEO-PI-R with 300, the IPIP big 5 with 100, the BFI with 44 items, the TIPI with 10) to include as part of other surveys.
6. Particularly an issue when using large (web based) surveys, there has been a tendency to develop short forms for surveys.

Many items versus many people

1. Not only do want many items, we also want many people.
2. Resolution (fidelity) goes up with sample size, N (standard errors are a function of $\sqrt{N}$)

$$\sigma_{\bar{x}} = \frac{\sigma_x}{\sqrt{N-1}} \qquad \sigma_r = \frac{1-r^2}{\sqrt{N-2}}$$

3. Also increases as number of items, n, measuring each construct (reliability as well as signal/noise ratio varies as number of items and average correlation of the items)

$$\lambda_3 = \alpha = \frac{n\bar{r}}{1+(n-1)\bar{r}} \qquad s/n = \frac{n\bar{r}}{(1-n\bar{r})}$$

4. Thus, we need to increase N as well as n. But how?

Subjects are expensive, so are items

1. In a survey such as Amazon's Mechanical Turk (MTURK), we need to pay by the person and by the item.
2. Why give each person the same items? Sample items, as we sample people.
3. Synthetically combine data across subjects and across items. This will imply a missing data structure which is
    - Missing Completely At Random (MCAR), or even more descriptively:
    - Massively Missing Completely at Random (MMCAR)
4. This is the essence of Synthetic Aperture Personality Assessment (SAPA) (Revelle, Wilt & Rosenthal, 2010; Revelle, Condon, Wilt, French, Brown & Elleman, 2016)

3 Methods of collecting 256 subject * items data

a) 8 x 32 complete

```
46213634521143453443645331212414
21243623166421516154432261516513
51661351155165463622224435623344
11141343362332215612152135614522
25353121264561433433232246526411
61335154566424114612641225353516
24634342151536242425413513435116
11554654453123111162423325516334
```

b) 32 x 8 complete

```
46323114
25443314
43315423
26314145
41435614
42236153
62421344
35234443
34514166
63415154
44441342
13514321
66365663
12264546
31466135
32645514
66151251
14411441
62443636
33316236
63325425
11531126
61155546
33245361
52241654
63212356
24414663
63661414
45555223
14364433
21461416
33232365
```

c) 32 x 32 MCAR p=.25

```
..3..2..6.....4.55.......44.....
...........4..6..45..3.4..6....1
6..3.......6.1.....6.2.......5.6
....3522......5.3...3......5....
....3.2.2.......3..2......65..5.
.....51...324..........23......5
....552............25...54.5....
...44.4.5....3..6...6........3..
....61.523.2....2...........3...
5.............42.4..6.5......61.
....3....3.6..1.4...1..5......5.
1....54..........2.4.33..6......
4.....52..6.....44.3...........2
..44...1........1..42....5..1...
..1..3.......2..3.521.......6...
.......3.142.........22......12.
.4...2..........3..162...4.....4
..4..6..3.4...1....5.33.........
5..........243..5....41......1..
..5..3..4...4.4..5..1.........4.
.....4.......3..5.2.....64.4..4.
...1.1.2...6....4......55....2..
.....3..2..53.....2..2.3.3......
......1...2..43...3.13........5.
...2.........4..54...2.3..62....
22.......332..1.....5......6....
...5..3.4.....3....5.241........
......63.1.......6...5..4..2...5
..2.4..5..........52.4.....44...
2.55.....2.....6.....6.....55...
..5..........4....6341.4..2.....
....55......5.......45....3..32.
```

Synthetic Aperture Personality Assessment

1. Give each participant a random sample of *pn* items taken from a larger pool of n items.
2. Find covariances based upon "pairwise complete data".
3. Find scales based upon basic covariance algebra.
   - Let the raw data be the matrix $\mathbf{X}$ with N observations converted to deviation scores.
   - Then the item variance covariance matrix is $\mathbf{C} = \mathbf{XX}'N^{-1}$
   - and scale scores, $\mathbf{S}$ are found by $\mathbf{S} = \mathbf{K}'\mathbf{X}$.
   - $\mathbf{K}$ is a keying matrix, with $\mathbf{K}_{ij} = 1$ if $item_i$ is to be scored in the positive direction for scale j, 0 if it is not to be scored, and -1 if it is to be scored in the negative direction.
   - In this case, the covariance between scales, $\mathbf{C}_s$, is

$$\mathbf{C}_s = \mathbf{K}'\mathbf{X}(\mathbf{K}'\mathbf{X})'N^{-1} = \mathbf{K}'\mathbf{XX}'\mathbf{K}N^{-1} = \mathbf{K}'\mathbf{CK}. \quad (1)$$

4. That is, we can find the correlations/covariances between scales from the item covariances, not the raw items.

SAPA is not magic: We can obtain high accuracy at the structure level but accuracy is much lower at the single subject level

1. Reliability of composite scales is high when formed from synthetic matrices $\mathbf{C}_s = \mathbf{K}'\mathbf{C}\mathbf{K}$ because the number of items per scale/per subject is the nominal amount.
2. Reliability of single scores is much less because very few items measuring a single trait are given to a single subject $\mathbf{S} = \mathbf{K}'\mathbf{X}$.
3. However, the precision of the estimate of subject means ($\bar{x}$) is high because $\sigma_{\bar{x}} = \frac{\sigma_x}{\sqrt{Np-1}}$ and Np is large.
4. SAPA technique is very powerful for research of structure, but less powerful for research based upon single subjects.
5. Particularly useful in web based surveys with many subjects when we are limited in the number of items we can administer and where we are trying to increase our domain validity.

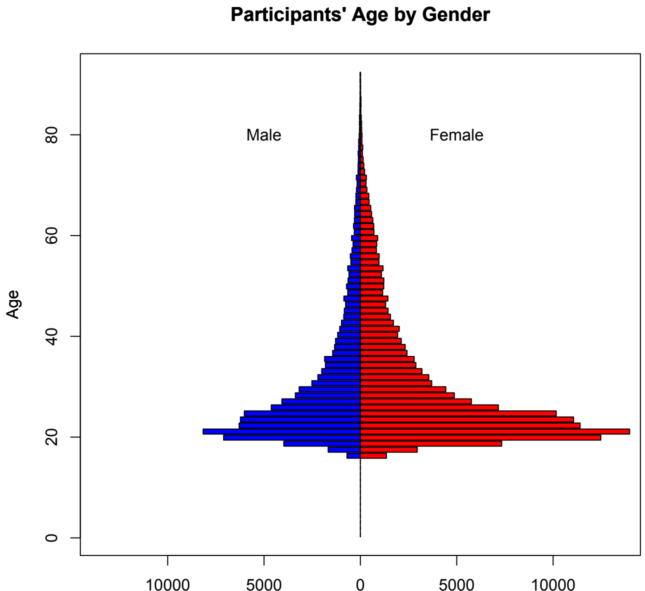
How does it work?

1. Give our basic belief in open science, we use public domain items, open source software:
   - Apache webserver, MySQL data bases, PHP and HTML5 web tools, R for statistics.
   - Extensive coding in PHP and MySQL to present item sets in random fashion (Joshua Wilt, David Condon, Jason French)
   - Code written for psychometric measurement and scale construction as implemented in the *psych* package (Revelle, 2016) using R (R Core Team, 2016)
2. Domains measured and item sources
   - Temperament items taken from International Personality Item Pool (IPIP) (Goldberg, 1999) (`ipip.ori.org`) and supplemented with other items.
   - Ability items have been validated (Condon & Revelle, 2014) as part of the International Cognitive Ability Resource Project (`ICAR-project.org`). (ICAR:Ability::IPIP:Temperament)
   - Interest items taken from Oregon Vocational Interest Survey (ORVIS) (Pozzebon, Visser, Ashton, Lee & Goldberg, 2010)

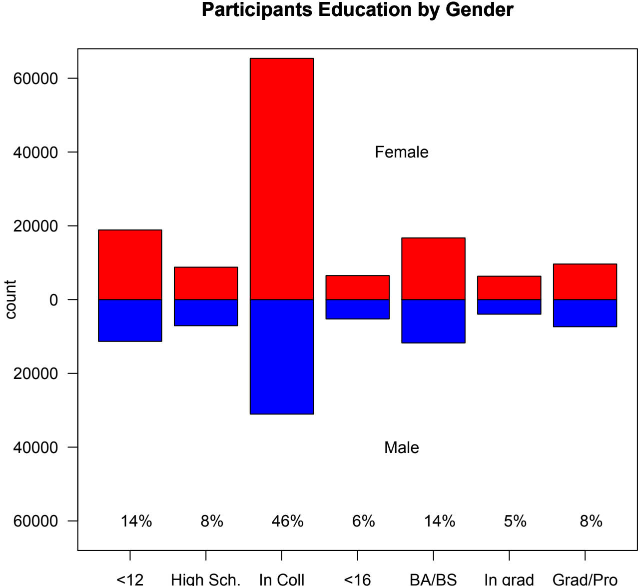
SAPA demographics

1. SAPA has been running for ≈ 10 years as either `personality-project.org` or now `sapa-project.org`.
2. We are reporting today on the last 6 years of data based upon 229,731 non-duplicated subjects.
3. In a poster present here by Lorien Elleman, we show that our results replicate differences between US states reported by Rentfrow (2010)
4. We have previously reported IQ data collected with SAPA as part of the International Cognitive Ability Resource project and released to the public domain (Condon & Revelle, 2014).
5. All analyses are done in the *psych* package (Revelle, 2016) in the open source statistical system R (R Core Team, 2016).

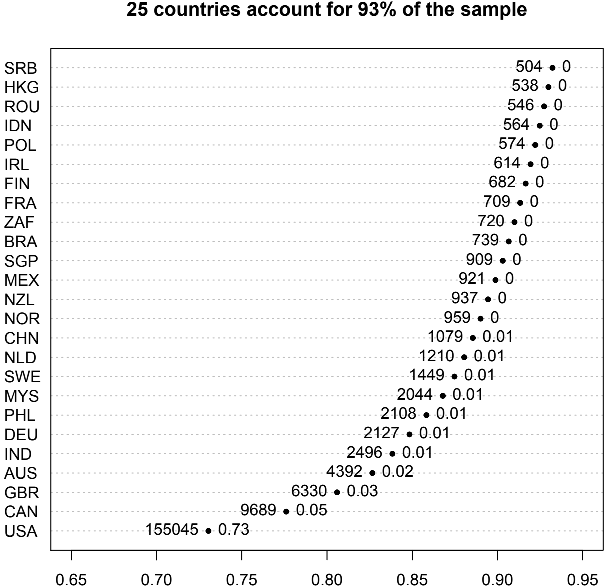
Mean age = 25.9 , Median = 22, IQR = 18 - 30



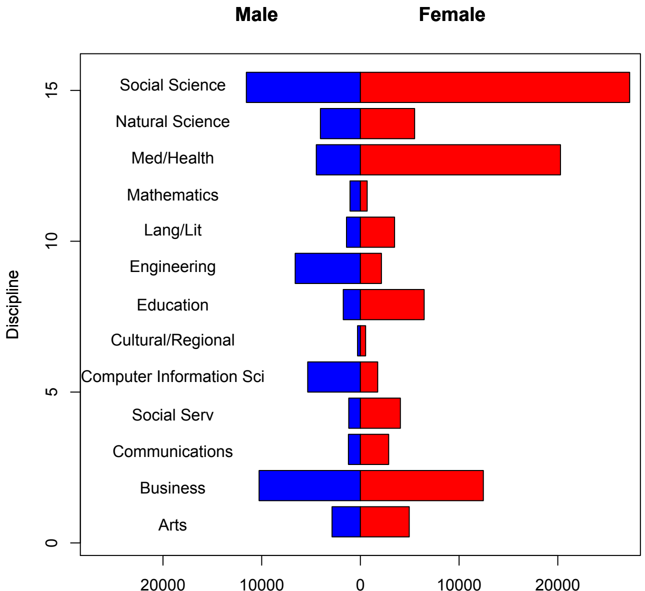
91% report their educational attainment.



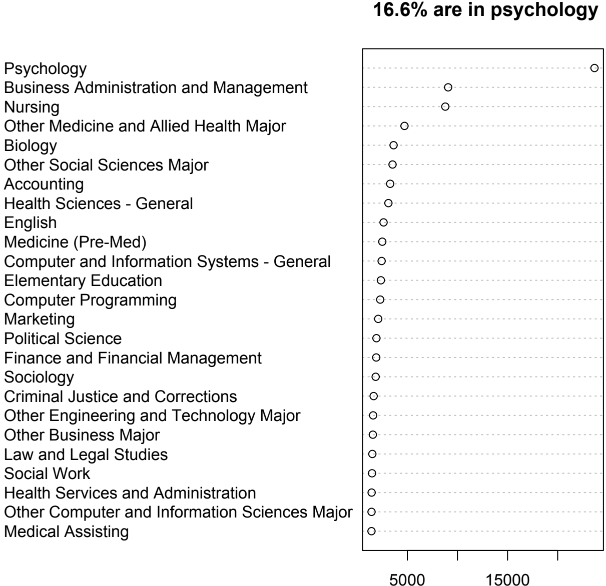
92% report country: of these 73% are US, 90% from 15 countries



62% report a college major. Majors by Discipline and Gender



25 majors account for 64% of those in or with college education



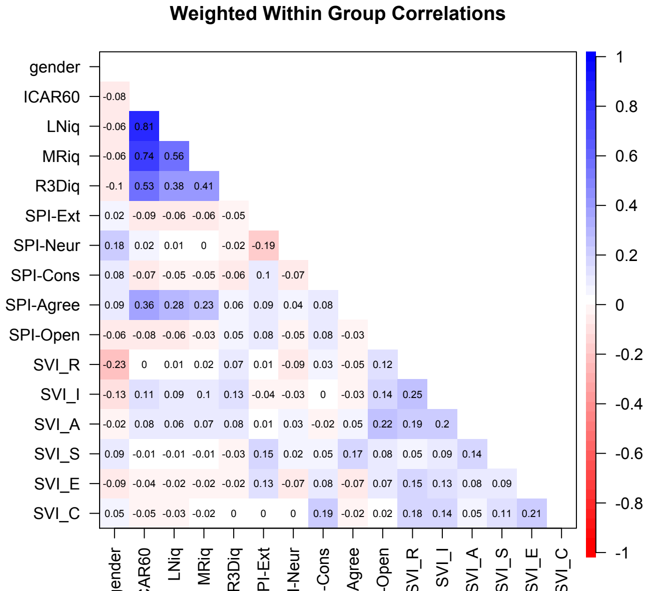
Temperament Items measures using the SAPA Personality Inventory

1. David Condon examined the 696 non-overlapping IPIP items that represent 18 different inventories (with 168 scales) that have what appear to be 1,894 items, In addition, those "magic 696" cover between 57% to 85% of 10 additional inventories with 235 additional scales (Condon, 2014).
2. David Condon has developed a short form of 135 items that provides coverage of 27 different narrow domains (Homogeneous Item Composites) as well as five broad factors corresponding as much as anyone else to the traditional Big 5.
3. We report here analyses of Temperament, Abilities and Interests by college major and reported occupation.
4. All scores are found using Item Response Theory scoring of items using a quasi-Rasch model, rather than a simple sum scores of items. These two methods agree almost perfectly without missing data, but the IRT approach is more powerful with our MMCAR data.

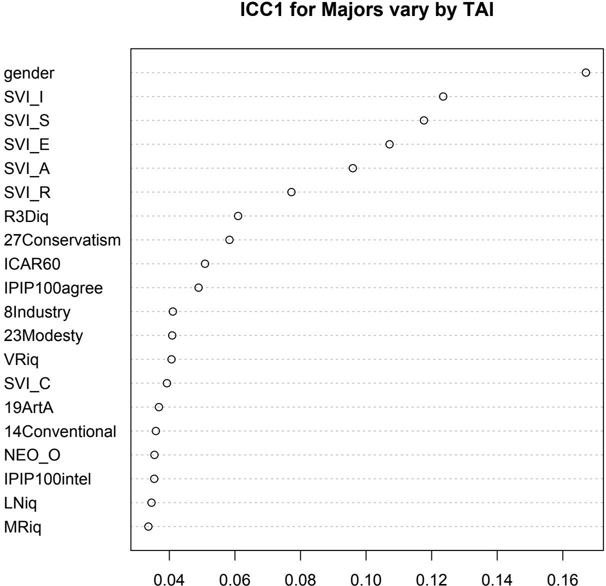
TAI for groups is not the same as TAI for individuals

1. How do occupational groups or college majors differ on TAI?
   - The mean scores for groups allow us to compare the groups
   - But it is the structure of these group means that are particularly interesting for they allow us to examine niche selection based upon peoples' aptitudes and appetites.
2. Overall correlation is a function of within group correlations and between group correlations.
3. Correlations of aggregate scores $r_{xy_{bg}}$ (between groups) $\neq$ aggregate of correlations $r_{xy_{wg}}$(within groups)
4. The overall correlation r_{xy} is a function of the within and the between correlations
   $r_{xy} = eta_{x_{wg}} * eta_{y_{wg}} * r_{xy_{wg}} + eta_{x_{bg}} * eta_{y_{bg}} * r_{xy_{bg}}$
5. These multi level correlations sometimes lead to what is known as the Yule-Simpson paradox (Kievit, Frankenhuis, Waldorp & Borsboom, 2013; Simpson, 1951; Yule, 1903)
   - These are independent and useful information.

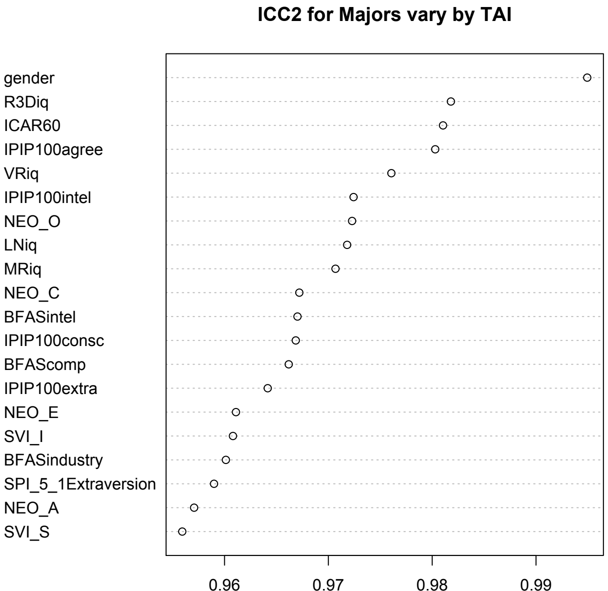
Within group correlations of Temperament, Ability, and Interests



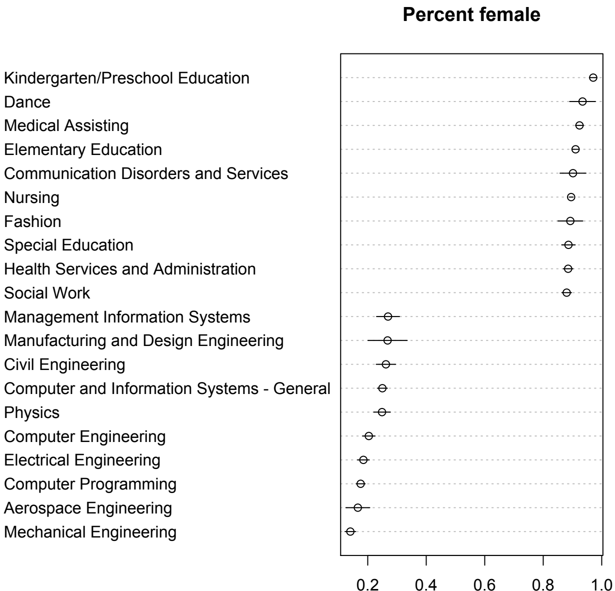
Majors: ICC1 refects the variance accounted for by group differences



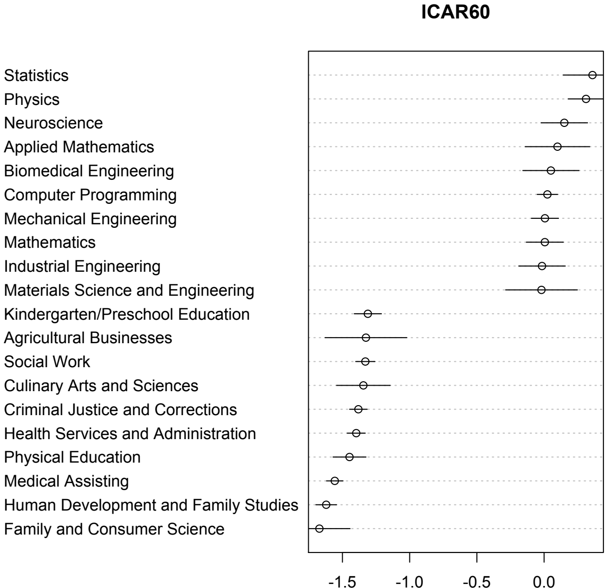
Majors: ICC2 reflects the reliability of the group differences



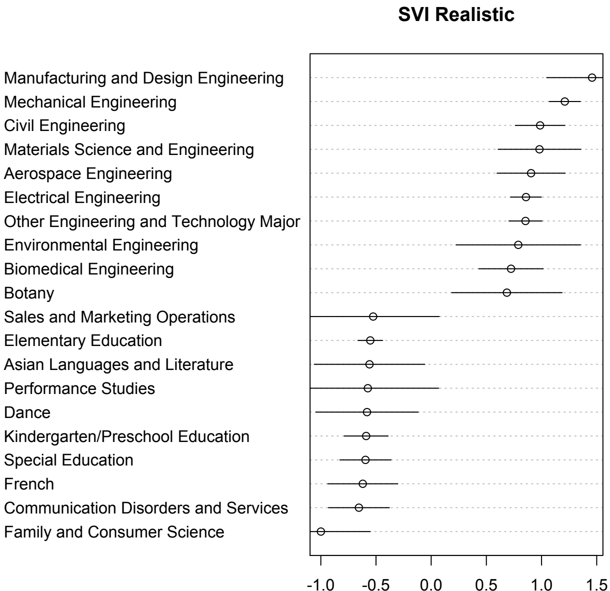
Majors differ the most in gender representation



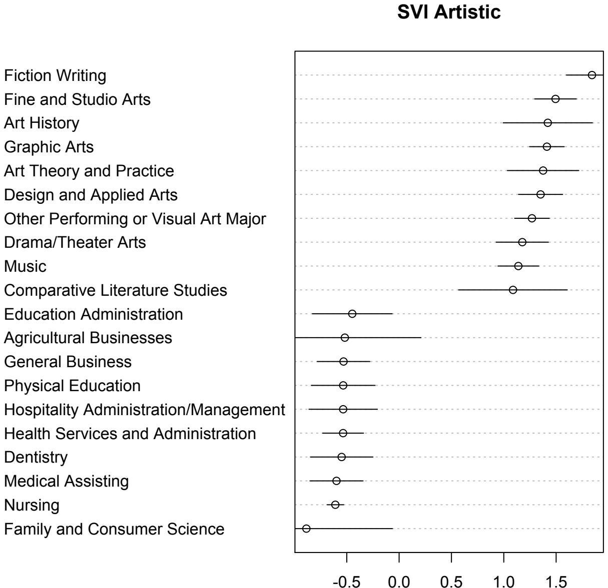
Ability difference between majors (with 95% confidence intervals)



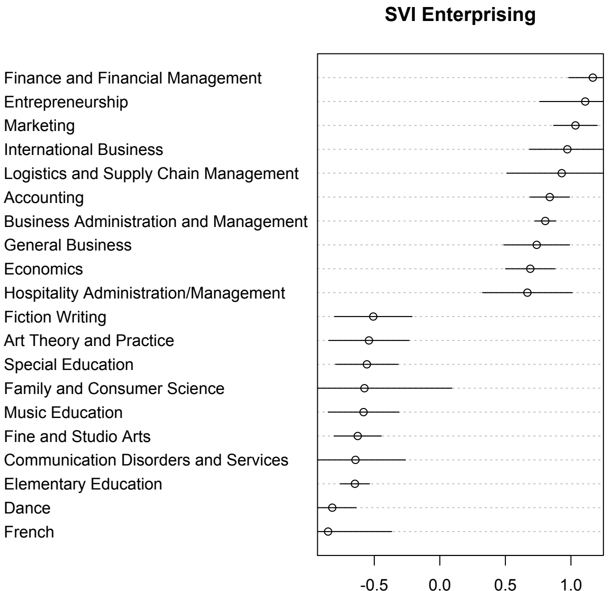
Realistic Interest differences between majors



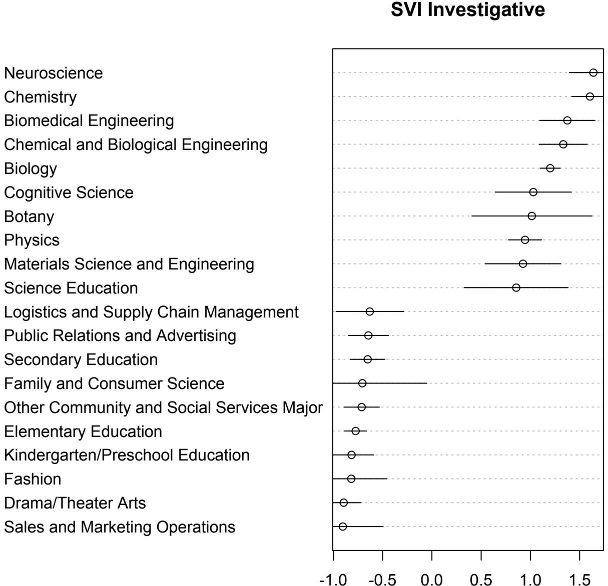
Artistic Interest difference between majors



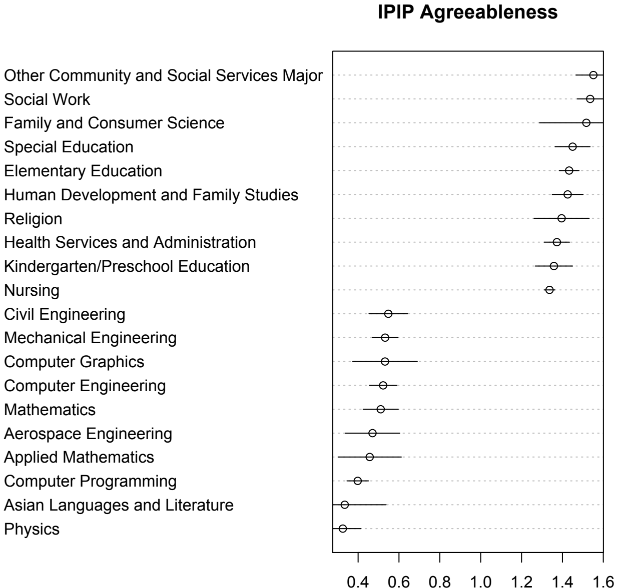
Enterprising Interest difference between majors



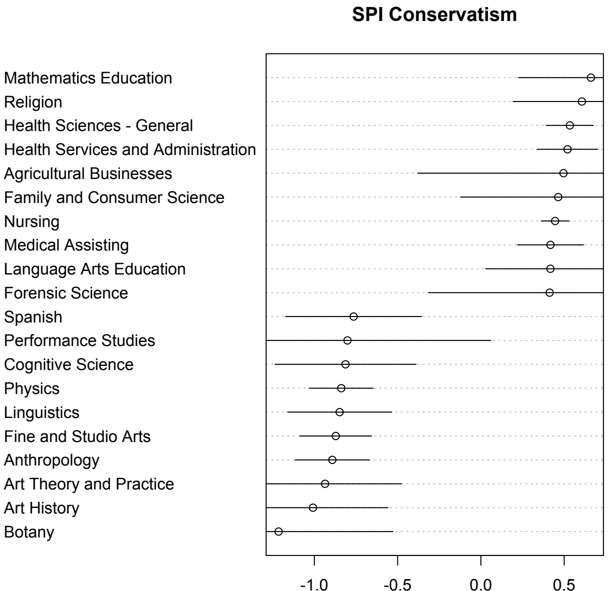
Investigative Interest difference between majors



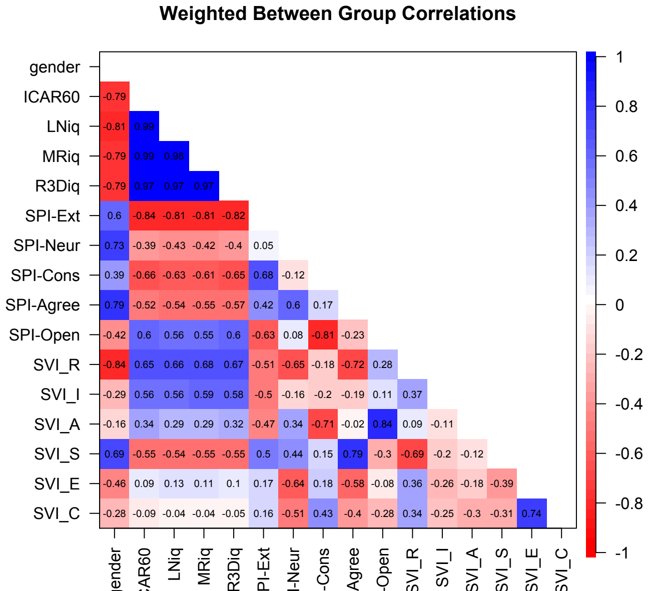
IPIP Agreeableness differs by major (with 95% confidence intervals)



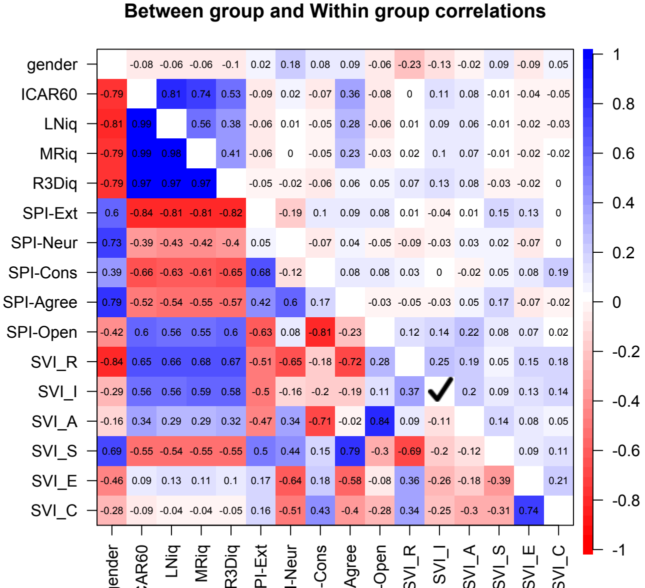
SPI conservative differs by major (with 95% confidence intervals)



Correlation of TAI between groups is different than within groups



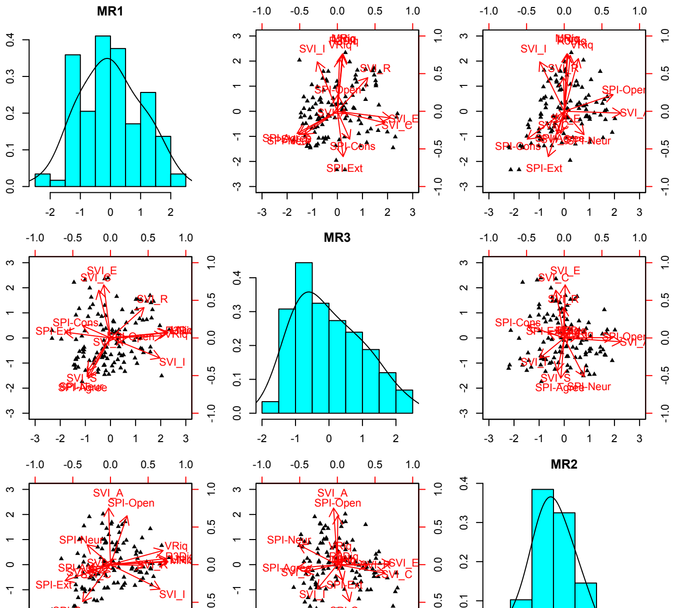
Comparing TAI between groups and within groups



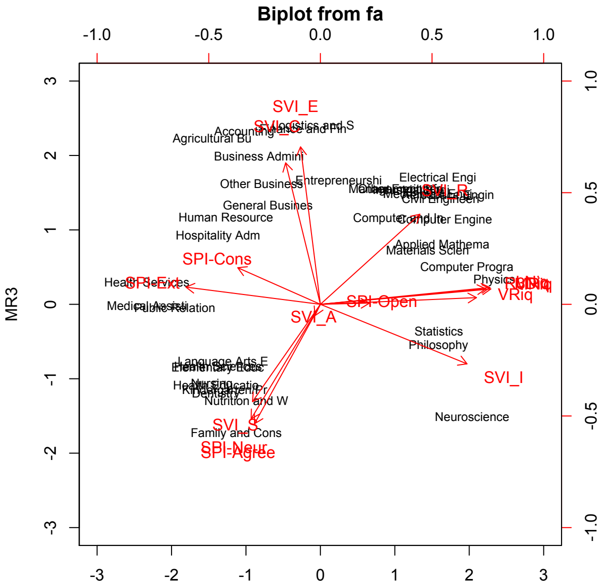
Interpreting these relationships

1. Students migrate into majors representing their strengths and interests
2. Majors choose students, (based upon ability?)
3. Student choose majors (based upon interests)
4. We can examine the factor structures of the between group correlations

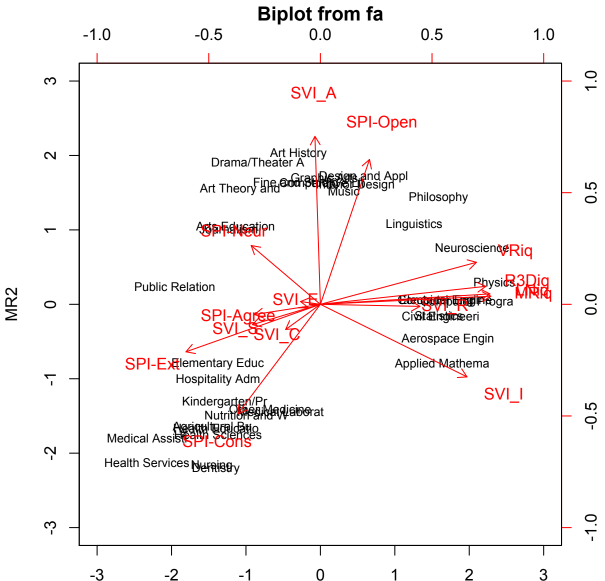
Factor structures of three dimensional between group solution



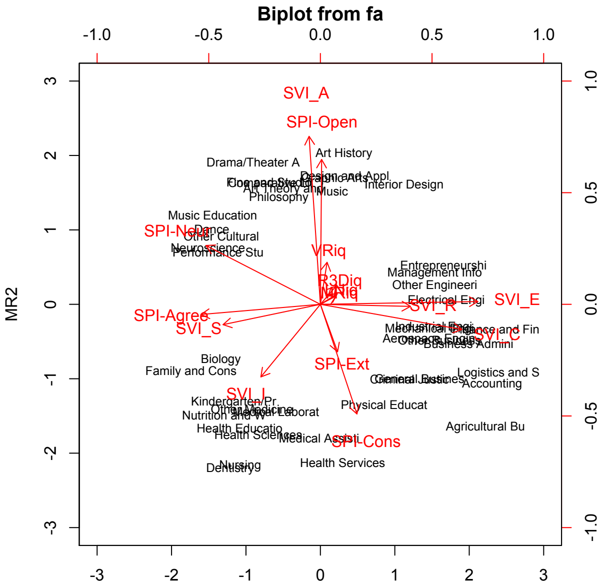
Biplot of dimensions 1 vs 2 for majors between group structure



Biplot of dimensions 1 vs. 3 for majors between group structure



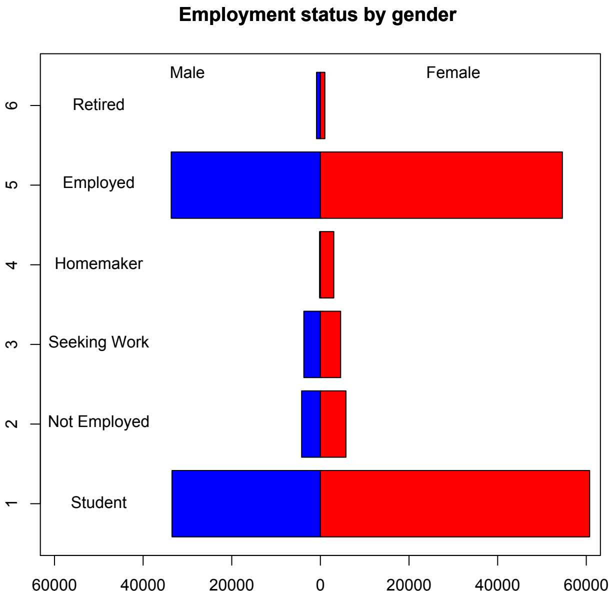
Biplot of dimensions 2 vs. 3 for majors between group structure



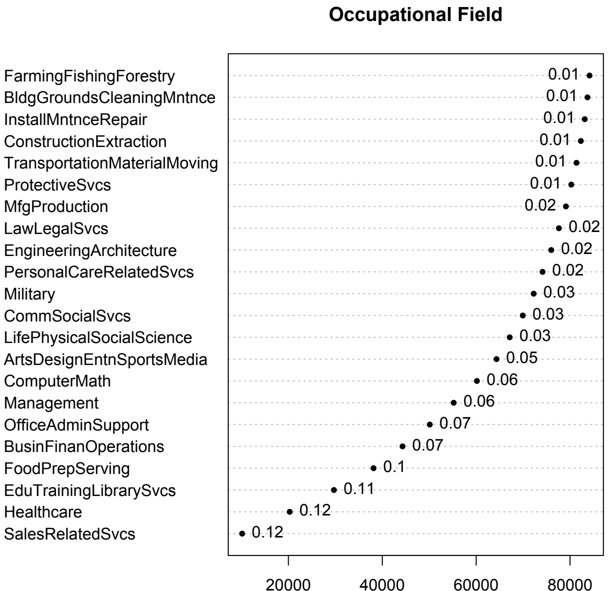
Similar results for occupations

1. Just as students selectively choose majors to represent their interests and abilities, so do people move into the work force to reflect their interests and abilities.
2. The large group differences we see in the average personality characteristics of college majors could reflect accentuation – people become like the others in the major and small original differences accentuate into the large differences we see.

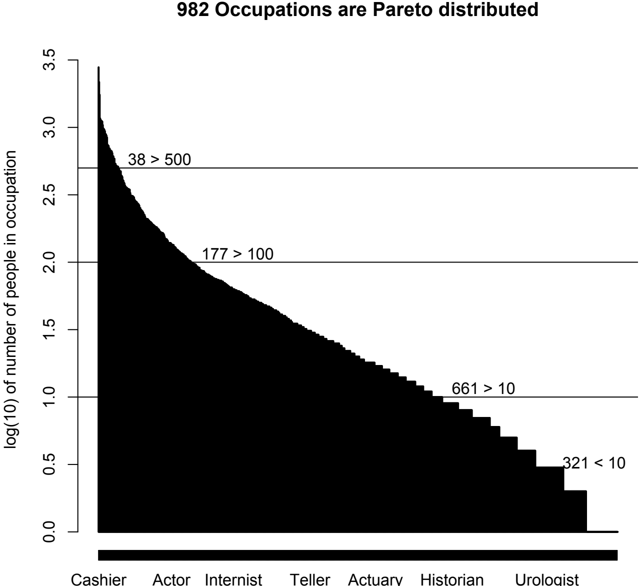
90% report their occupational status: Occupational status by Gender



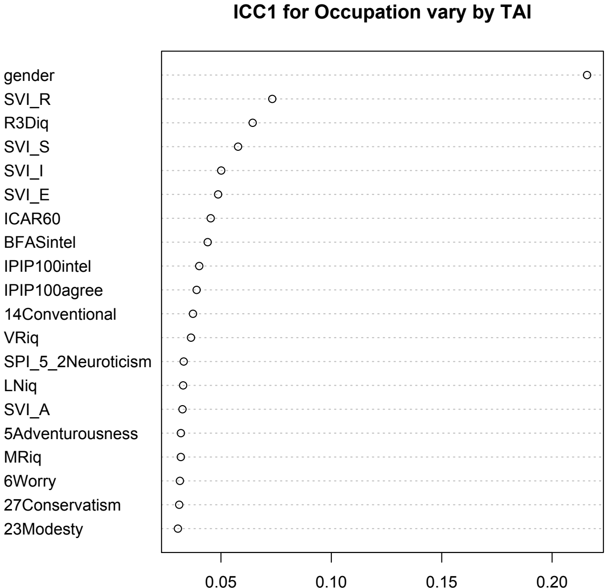
Broad Occupational "Field"



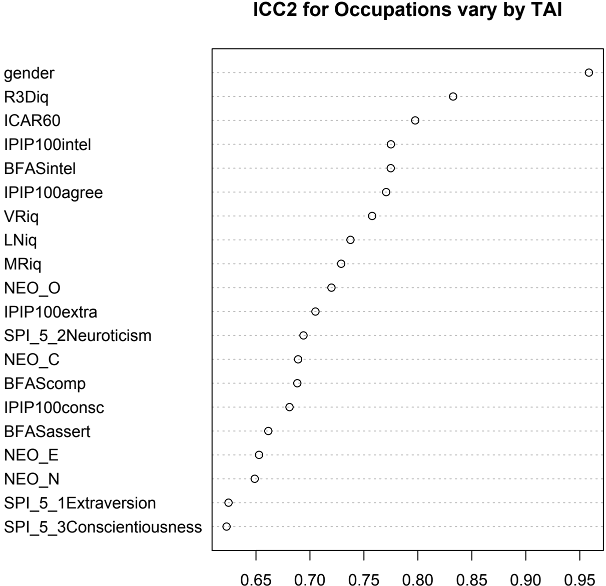
Occupations are Pareto distributed with 80% in top 20%



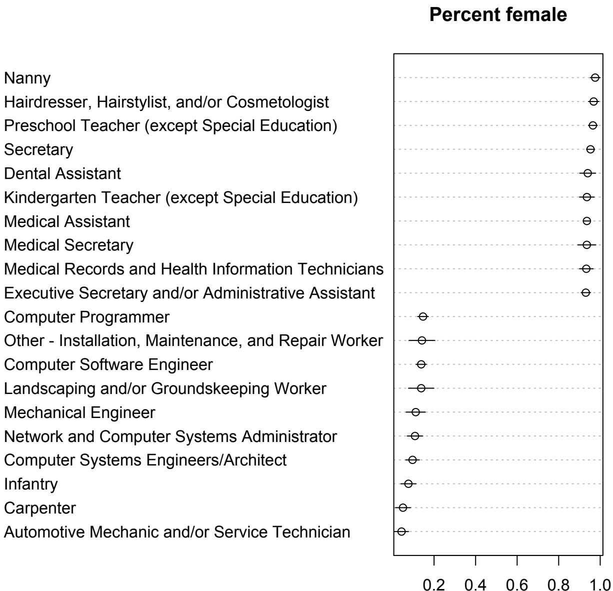
Occupations: ICC1 = variance accounted for by group differences



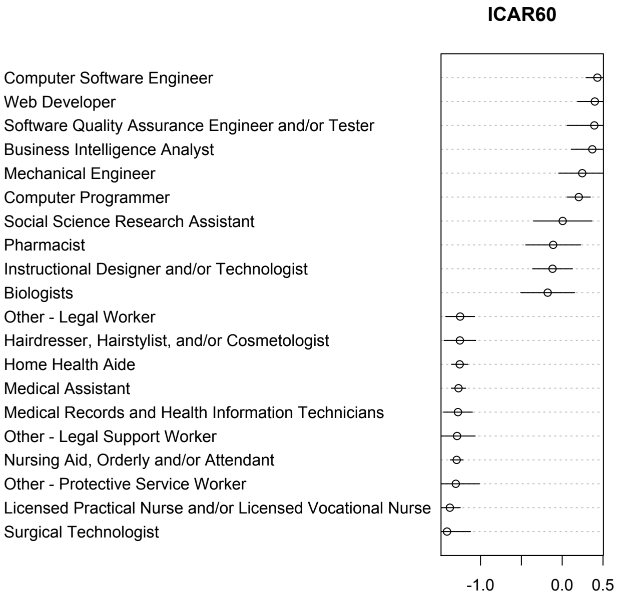
Occupations: ICC2 = reliability of group differences



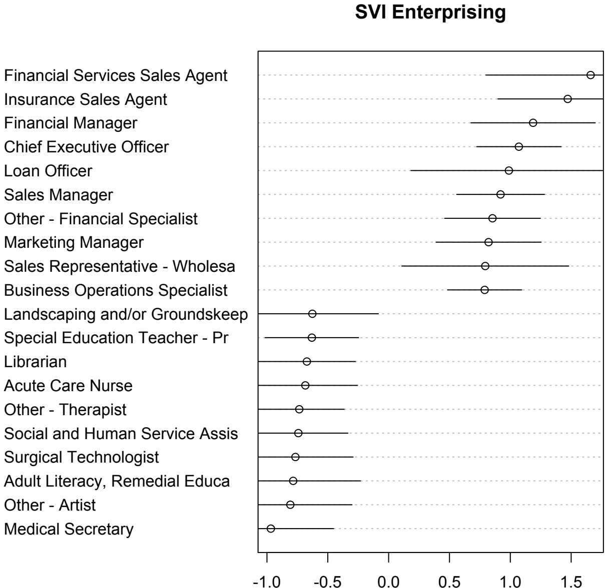
Occupations differ by ability: top and bottom by gender



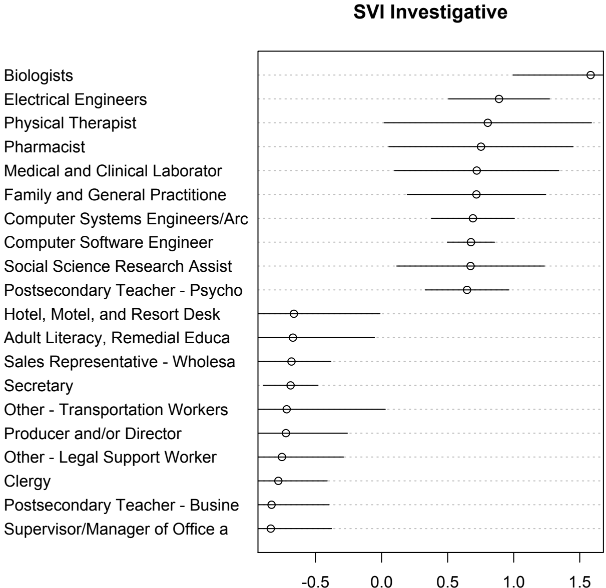
Occupations differ by ability: top and bottom by ICAR60



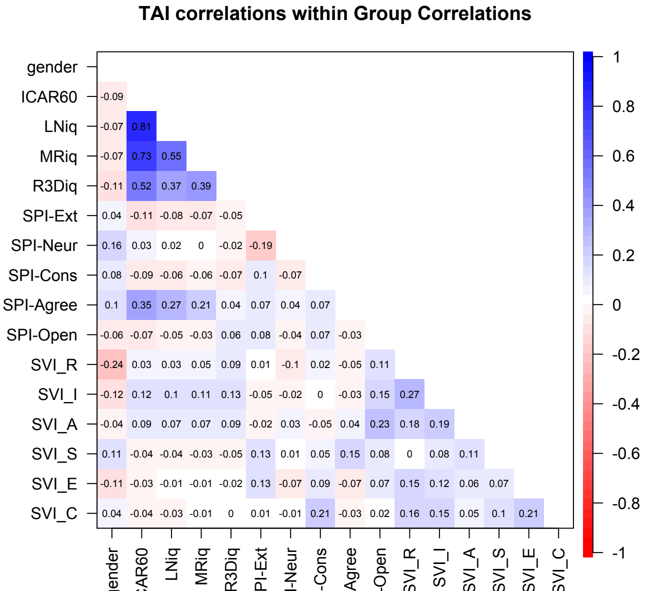
Occupations differ by ability: top and bottom by SVI Enterprising



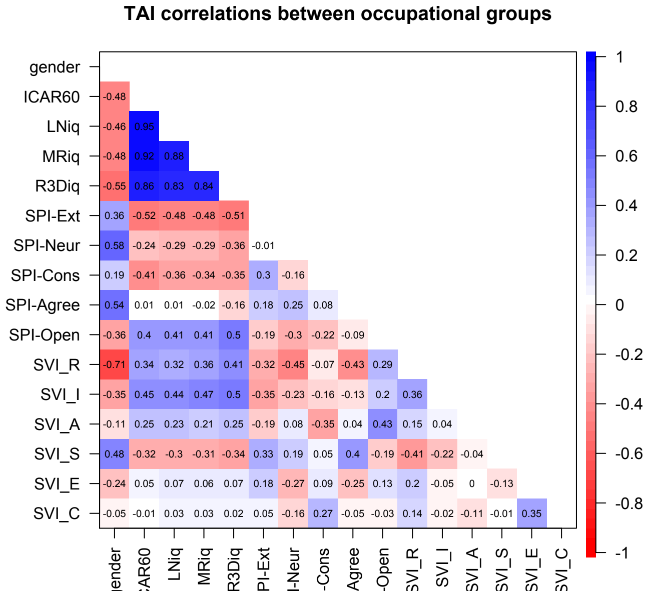
Occupations differ by ability: top and bottom by SVI Investigative



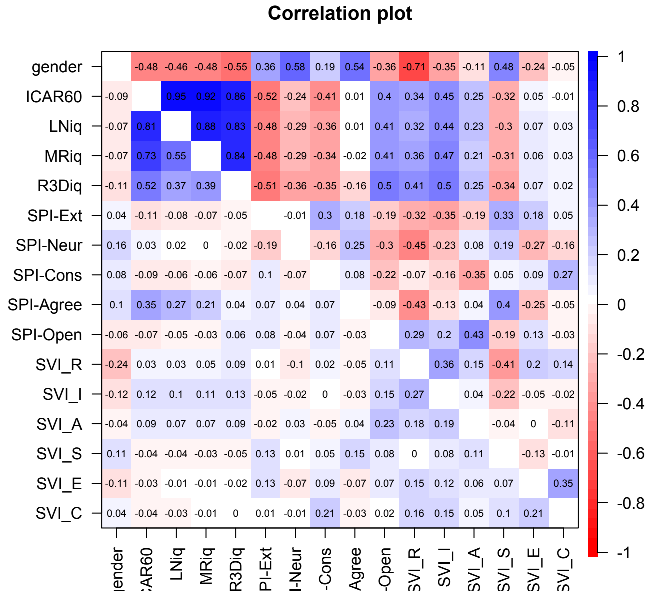
Within group correlational structure is the conventional solution



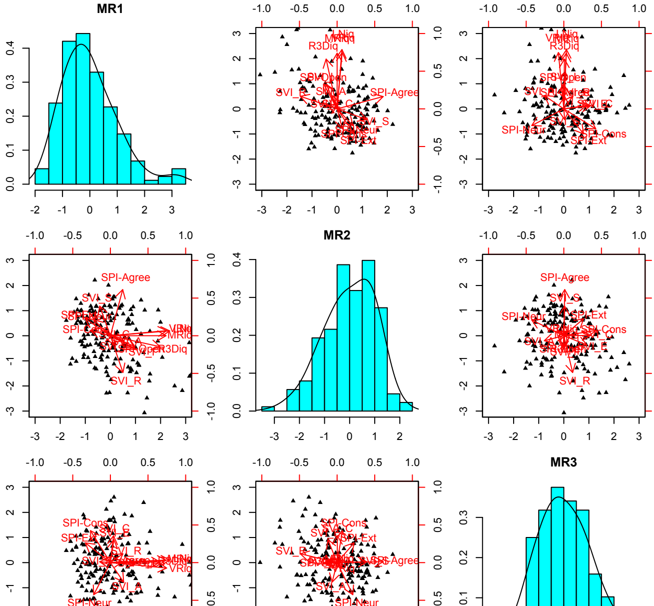
Between group correlations show a very different structure



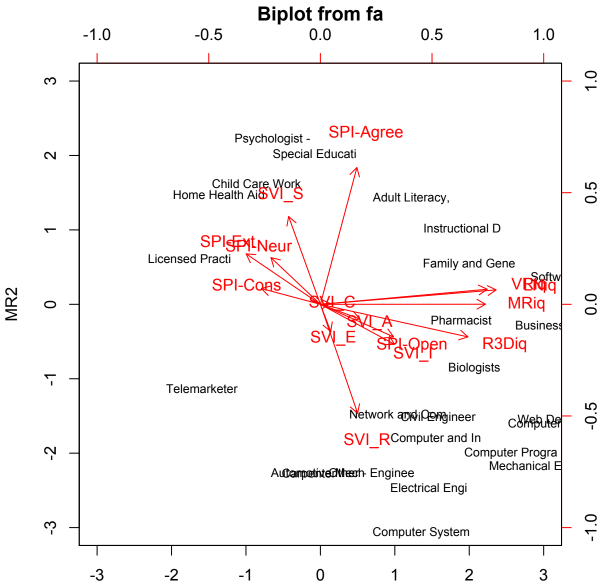
Compare the within group and between group correlations



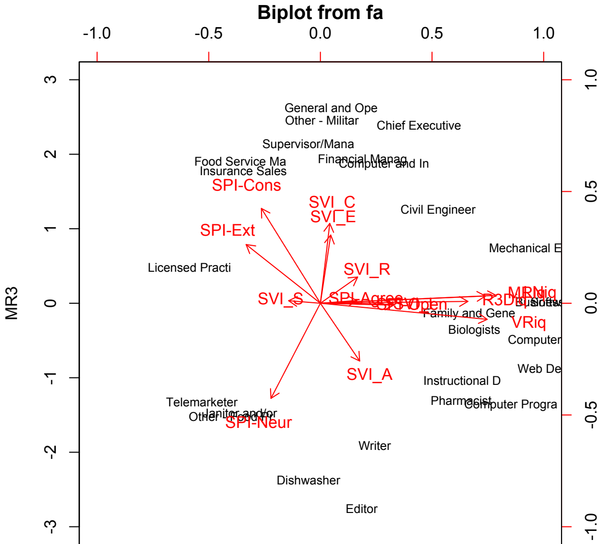
Factor structures of three dimensional between group solution



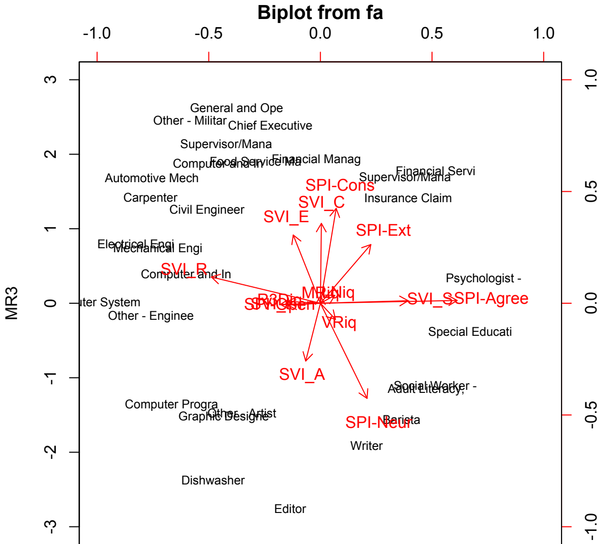
Biplot of dimensions 1 vs 2 for occupations between group structure



Biplot of dimensions 1 vs. 3 for occupations between group structure



Biplot of dimensions 2 vs. 3 for occupations between group structure



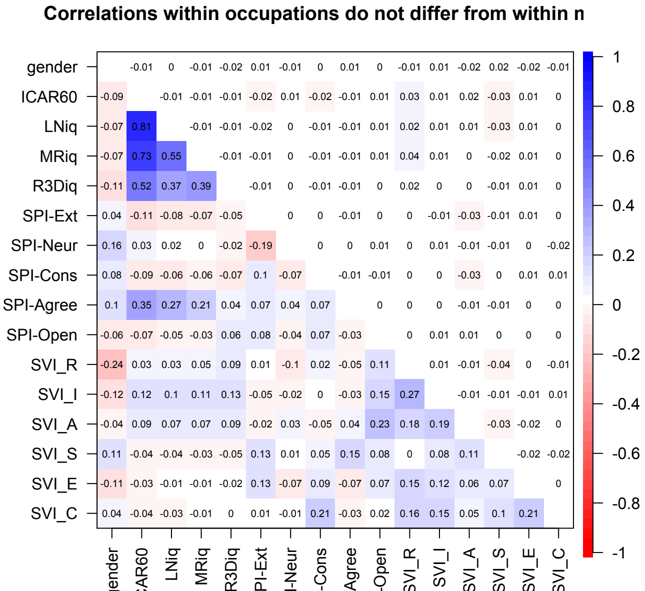
Expanding the Personality toolbox: Abilities and Interest

1. When predicting real world outcomes such as choice of college major or occupation, it is important to go beyond traditional personality measures.
2. Ability serves as filter to college majors and occupations
3. Interests direct choice between majors and occupations.
4. Personality, ability and temperament structures at group level are very different than those within groups.

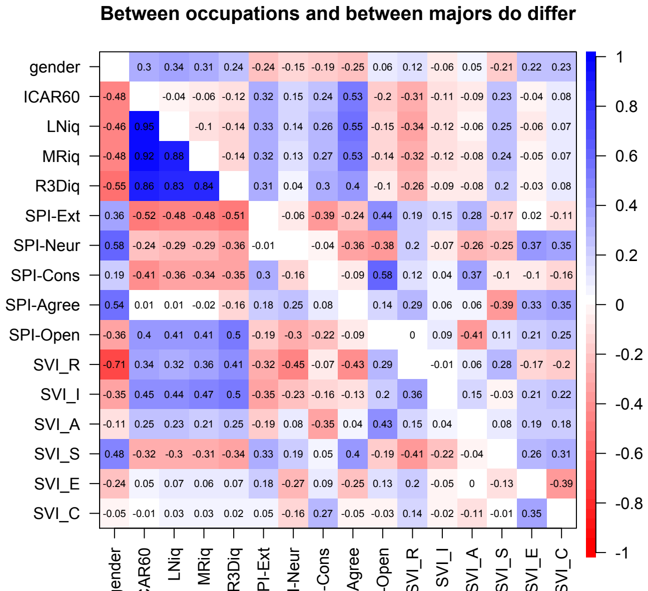
More information

1. Slides are at
   http://personality-project.org/sapa.html
2. Ability measures are taken from the International Cognitive Ability Resource (Condon & Revelle, 2014)
   (see http://icar-project.com)
3. Data sets are available at DataVerse: (Condon & Revelle, 2015).
4. Analytical code done using the *psych* package (Revelle, 2016) in R (R Core Team, 2016).

Compare the within group correlations for occupations and majors



Compare the between group correlations for occupations and majors



The following is not included as slides but is included in the pdf to help see how to do the analysis.

First, some basic descriptives

R code

```
tedu <- table(demo.TAI$education)
totedu <- sum(!is.na(demo.TAI$education))
tedu/totedu
with(demo.TAI,bi.bars(age,as.numeric(gender),main="Participants' Age I
 text(-5000,80,"Male")
text(5000,80,"Female")
with(demo.TAI,bi.bars(education,as.numeric(gender)))
with(demo.TAI,bi.bars(as.numeric(education),as.numeric(gender),horiz=I
text(5,40000,"Female")
text(5,-40000,"Male")

 text(.8,-60000,"14%")
 text(2,-60000,"8%")
text(3.2,-60000,"46%")
 text(4.4,-60000,"6%")
text(5.6,-60000,"14%")
text(6.8,-60000,"5%")
text(8,-60000,"8%")
```

```
sum(!is.na(demo.TAI$education))/nrow(demo.TAI)

tc <- table(demo.TAI$country)
totc <- sum(!is.na(demo.TAI$country))
tcs <- sort(tc,TRUE)
dotchart(tcs[2:35],main="Count by country (US = 155,045 not shown)")
for (i in 3:35) {text(tcs[i],i-1,tcs[i],pos=4)}
text(tcs[2],1,tcs[2],pos=2)


ctcs <- cumsum(tcs)
dotchart(ctcs[1:25]/totc,main="25 countries account for 93% of the sa
#text(ctcs[1]/tot,1,tcs[1],pos=4)
 for (i in 1:25) {text(ctcs[i]/totc,i,tcs[i],pos=2)
text( ctcs[i]/totc,i,round(tcs[i]/totc,2), pos=4)
 }
 tcs[1]/tot
 ctcs[10]/tot

disc.name <- c("Arts","Business","Communications","Social Serv","Comp
 with(demo.TAI,bi.bars(as.numeric(discipline),as.numeric(gender),hori
 for(i in 1:13){
 text(-19000,(i-.5)*15.8/13,disc.name[i],srt=0)}
```

```
 with(demo.TAI,bi.bars(as.numeric(jobstatus),gender,horiz=TRUE,main =
job.names <- c("Student", "Not Employed","Seeking Work","Homemaker","I
for(i in 1:6) {text( -50000,(i-.4) * 6/5,job.names[i],srt=00)}
text(-30000,7.2,"Male")
text(30000,7.2,"Female")
sum(!is.na(demo.TAI$jobstatus))/nrow(demo.TAI)


maj <- table(demo.TAI$major)
maj <- sort(maj,TRUE)
dotchart(maj[25:1],main=" 16.6% are in psychology"))
cmaj <- cumsum(maj)
tot <- sum(maj)
pmaj<- cmaj/tot
tot/nrow(demo.TAI)
sum(maj > 100)

plot(cmaj,xlab="College Major",ylab="Cumulative number of majors")

plot(log10(maj),xlab="College Major",ylab="Log (10) of number in  majo
abline(h=3)
abline(h=2)
text(118,2.05,"118 > 100 ", pos=4)
text(38,3.05,"38 > 1,000",pos=4)
```

```
abline(h=log10(500))
text(68,log10(500)+.05,"68 > 500",pos=4)


jf <- table(demo.TAI$jobfield)
jf <- sort(jf,TRUE)
cjf <- cumsum(jf)
 totjf

dotchart(cjf,main = "Occupational Field", pch=20)
for(i in 1:15) {text(cjf[i],i, round(jf[i]/totjf,2), pos=4)}
for(i in 16:22) {text(cjf[i],i, round(jf[i]/totjf,2), pos=2)}


occ <- table(demo.TAI$occupation)
%
 occ <- sort(occ,TRUE)
plot(log10(occ[1:200]),main="Top 200 occupations account for  80% of p
 abline(h=log10(100))
 text(177,log10(100)+.05, "177 > 100", pos=4)
 abline(h=log10(500))
text(38,log10(500)+.05,"38 > 500",pos=4)

plot(log10(occ),main="982 Occupations are Pareto distributed",ylab="lo
abline(h=log10(100))
```

```
 text(177,log10(100)+.05, "177 > 100", pos=4)
 abline(h=log10(500))
text(38,log10(500)+.05,"38 > 500",pos=4)
abline(h=log10(10))
text(651,1.05,"661 > 10", pos=4)

text(860,.5,"321 < 10",pos=4)
```

Now, lets do it by major

R code

```
sb.demo.TAI <- statsBy(demo.TAI[c(1:30,36:93)],group="major")
 names(sb.demo.TAI)
 [1] "mean"   "sd"     "n"      "F"      "ICC1"   "ICC2"   "raw"    "rbg"    "
>

icc1 <- sb.demo.TAI$ICC1
 names(icc1) <- sub(".theta","",names(icc1))
 names(icc1) <- sub("SPI_27_","",names(icc1))
 icc1.p <- icc1[-c(1:10,12:25)]
 dotchart(sort(icc1.p)[c(45:64)],main="ICC1 for Majors vary by TAI")

 icc2 <- sb.demo.TAI$ICC2
```

```
 names(icc2) <- sub(".theta","",names(icc2))
 names(icc2) <- sub("SPI_27_","",names(icc2))
 icc2.p <- icc2[-c(1:10,12:25)]
 dotchart(sort(icc2.p)[c(45:64)],main="ICC2 for Majors vary by TAI")




maj.mean <- sb.demo.TAI$mean
maj.n    <- sb.demo.TAI$n
maj.sd <- sb.demo.TAI$sd




colnames(maj.mean) <- sub(".theta","",colnames(maj.mean))
colnames(maj.mean) <- sub("SPI_27_","",colnames(maj.mean))
colnames(maj.sd) <- sub("SPI_27_","",colnames(maj.sd))
colnames(maj.sd) <- sub(".theta","",colnames(maj.sd))
maj.se <- maj.sd /sqrt(maj.n)

maj.mean100 <- subset(maj.mean,(maj.n[,26] > 99))
maj.n100 <- subset(maj.n,(maj.n[,26] > 99))
maj.sd100 <-  subset(maj.sd,(maj.n[,26] > 99))
maj.se.100 <- subset(maj.se,(maj.n[,26] > 99))
```

```
maj.data <- list(mean=maj.mean100,n = maj.n100,sd = maj.sd100)

ord  <- order(maj.mean100[,"gender"])
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"gender"]-1,maj.se.10
ord  <- order(maj.mean100[,"ICAR60"])
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"ICAR60" ],maj.se.100
dotchart(sort(maj.mean100[,"ICAR60"])[c(1:10,108:117)], main="ICAR 60
ord  <- order(maj.mean100[,"SVI_I"])
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"SVI_I" ],maj.se.100[
 #dotchart(sort(maj.mean100[,"SVI_I"])[c(1:10,108:117)], main="SVI In
 ord  <- order(maj.mean100[,"SVI_E"])
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"SVI_E" ],maj.se.100[

 #dotchart(sort(maj.mean100[,"SVI_E"])[c(1:10,108:117)], main="SVI Ent

 ord  <- order(maj.mean100[,"SVI_A"])
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"SVI_A" ],maj.se.100[
#  dotchart(sort(maj.mean100[,"SVI_A"])[c(1:10,108:117)], main="SVI A

ord  <- order(maj.mean100[,"SVI_R"])
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"SVI_R"],maj.se.100[o

# dotchart(sort(maj.mean100[,"SVI_R"])[c(1:10,108:117)], main="SVI Rea

ord  <- order(maj.mean100[,"27Conservatism"])
```

```
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"27Conservatism"],maj

dotchart(sort(maj.mean100[,"27Conservatism"])[c(1:10,108:117)], main="

ord  <- order(maj.mean100[,"IPIP100agree"])
dotchart.psych(maj.mean100[ord[c(1:10,108:117)],"IPIP100agree"],maj.se
dotchart(sort(maj.mean100[,"IPIP100agree"])[c(1:10,108:117)], main="IP

rbg.maj <- sb.demo.TAI$rbg
 colnames(rbg.maj) <- rownames(rbg.maj) <- sub(".theta.bg","",colnames
  colnames(rbg.maj) <- rownames(rbg.maj)  <- sub("SPI_27_","",colnames
  colnames(rbg.maj) <- rownames(rbg.maj)  <- sub("SPI_5_","",colnames
    colnames(rbg.maj) <- rownames(rbg.maj)  <- sub(".bg","",colnames(r
  colnames(rbg.maj)[57:61] <- c("SPI-Ext","SPI-Neur","SPI-Cons","SPI-A
  colnames(rbg.maj) <- rownames(rbg.maj) <-  sub("IPIP100","IPIP",coln
   rownames(rbg.maj) <-  colnames(rbg.maj)

 corPlot(rbg.maj[c(10,25:28,57:61,82:87),c(10,25:28,57:61,82:87)],uppe


 rwg.maj<- sb.demo.TAI$rwg
 colnames(rwg.maj ) <- rownames(rwg.maj ) <- sub(".theta.wg","",colnam
  colnames(rwg.maj) <- rownames(rwg.maj)  <- sub("SPI_27_","",colnames
  colnames(rwg.maj) <- rownames(rwg)  <- sub("SPI_5_","",colnames(rwg)
    colnames(rwg.maj) <- rownames(rwg.maj)  <- sub(".wg","",colnames(r
```

```
    colnames(rwg.maj)[57:61] <- c("SPI-Ext","SPI-Neur","SPI-Cons","SPI
     rownames(rwg.maj) <-  colnames(rwg.maj)
 corPlot(rwg.maj[c(10,25:28,57:61,82:87),c(10,25:28,57:61,82:87)],uppe




maj.up.low <-lowerUpper(lower=rbg[c(10,25:28,57:61,82:87),c(10,25:28,5
 corPlot(maj.up.low,numbers=TRUE,main="Between group and Within group
```

What about the factor structure of TAI between groups.

R code

```
f3.bg<- fa(rbg[c(26:29,57:61,82:87),c(26:29,57:61,82:87)],3)

ov <- c(26:29,57:61,82:87)
f3.bg <- fa(rbg.maj[ov,ov],3)
maj.f3.scores <- factor.scores(maj.mean100[,ov+1],f3.bg)  #because the
maj.names <- rownames(f3.bg$scores$scores)
maj.names <-  substr(maj.names,1,15)

f3.bg$scores <- maj.f3.scores
biplot(f3.bg,labels=maj.names,choose=c(1,2),cuts=1.5)
biplot(f3.bg,labels=maj.names,cuts=1.5)
```

Now, for occupation: Basically just a repeat of the major procedures

R code

```
sb.demo.TAI.occ <- statsBy(demo.TAI[c(1:30,36:93)],group="occupation")
icc1 <- sb.demo.TAI.occ$ICC1
names(icc1) <- sub(".theta","",names(icc1))
 names(icc1) <- sub("SPI_27_","",names(icc1))
 icc1.p <- icc1[-c(1:10,12:25)]
 dotchart(sort(icc1.p)[c(45:64)],main="ICC1 for Occupation vary by TAI


  icc2 <- sb.demo.TAI.occ$ICC2
 names(icc2) <- sub(".theta","",names(icc2))
 names(icc2) <- sub("SPI_27_","",names(icc2))
 icc2.p <- icc2[-c(1:10,12:25)]
 dotchart(sort(icc2.p)[c(45:64)],main="ICC2 for Occupations vary by TA


 occ.mean <- sb.demo.TAI.occ$mean
occ.n    <- sb.demo.TAI.occ$n
occ.sd <- sb.demo.TAI.occ$sd
```

```
colnames(occ.mean) <- sub(".theta","",colnames(occ.mean))
colnames(occ.mean) <- sub("SPI_27_","",colnames(occ.mean))
colnames(occ.sd) <- sub("SPI_27_","",colnames(occ.sd))
colnames(occ.sd) <- sub(".theta","",colnames(occ.sd))
occ.se <- occ.sd /sqrt(occ.n)

occ.mean100 <- subset(occ.mean,(occ.n[,26] > 99))
occ.n100 <- subset(occ.n,(occ.n[,26] > 99))
occ.sd100 <-  subset(occ.sd,(occ.n[,26] > 99))
occ.se.100 <- subset(occ.se,(occ.n[,26] > 99))

occ.names <- rownames(occ.mean100)
occ.names <-  substr(occ.names,1,30)
rownames(occ.mean100) <- occ.names


occ.data <- list(mean=occ.mean100,n = occ.n100,sd = occ.sd100)
n.occ <- 176
ord  <- order(occ.mean100[,"gender"])
dotchart.psych(occ.mean100[ord[c(1:10,(n.occ-9):n.occ)],"gender"]-1,oc
ord  <- order(occ.mean100[,"ICAR60"])
dotchart.psych(occ.mean100[ord[c(1:10,(n.occ-9):n.occ)],"ICAR60" ],occ
```

```
ord  <- order(occ.mean100[,"ICAR60"],decreasing=TRUE)
dotchart.psych(occ.mean100[ord[20:1],"ICAR60"],occ.se.100[ord[1:20],"I
dotchart(sort(occ.mean100[,"ICAR60"])[c(1:10,(n.occ-9):n.occ)], main='
ord  <- order(occ.mean100[,"SVI_I"])
dotchart.psych(occ.mean100[ord[c(1:10,(n.occ-9):n.occ)],"SVI_I" ],occ
 #dotchart(sort(occ.mean100[,"SVI_I"])[c(1:10,(n.occ-9):n.occ)], main=
 ord  <- order(occ.mean100[,"SVI_E"])
dotchart.psych(occ.mean100[ord[c(1:10,(n.occ-9):n.occ)],"SVI_E" ],occ

rbg.occ <- sb.demo.TAI.occ$rbg
 colnames(rbg.occ) <- rownames(rbg.occ) <- sub(".theta.bg","",colnames
  colnames(rbg.occ) <- rownames(rbg.occ)  <- sub("SPI_27_","",colnames
  colnames(rbg.occ) <- rownames(rbg.occ)  <- sub("SPI_5_","",colnames
    colnames(rbg.occ) <- rownames(rbg.occ)  <- sub(".bg","",colnames(r
  colnames(rbg.occ)[57:61] <- c("SPI-Ext","SPI-Neur","SPI-Cons","SPI-A
  colnames(rbg.occ) <- rownames(rbg.occ) <-  sub("IPIP100","IPIP",coln
   rownames(rbg.occ) <-  colnames(rbg.occ)

  rwg.occ <- sb.demo.TAI.occ$rwg
 colnames(rwg.occ) <- rownames(rwg.occ) <- sub(".theta.bg","",colnames
  colnames(rwg.occ) <- rownames(rwg.occ)  <- sub("SPI_27_","",colnames
  colnames(rwg.occ) <- rownames(rwg.occ)  <- sub("SPI_5_","",colnames
    colnames(rwg.occ) <- rownames(rwg.occ)  <- sub(".bg","",colnames(r
  colnames(rwg.occ)[57:61] <- c("SPI-Ext","SPI-Neur","SPI-Cons","SPI-A
  colnames(rwg.occ) <- rownames(rwg.occ) <-  sub("IPIP100","IPIP",coln
```

```
   rownames(rwg.occ) <-  colnames(rwg.occ)
corPlot(rbg.occ[c(10,25:28,57:61,82:87),c(10,25:28,57:61,82:87)],uppe
corPlot(rwg.occ[c(10,25:28,57:61,82:87),c(10,25:28,57:61,82:87)],uppe
occ.upperlower <-  lowerUpper(rwg.occ[c(10,25:28,57:61,82:87),c(10,25
corPlot(occ.upperlower,numbers=TRUE)
```

Now, a few comparisons of grouping by major and grouping by occupatio

R code

```
occ.maj.upperlower <-  lowerUpper(rwg.occ[c(10,25:28,57:61,82:87),c(1
corPlot

occ.maj.upperlower <-  lowerUpper(rwg.occ[c(10,25:28,57:61,82:87),c(1
corPlot(occ.maj.upperlower,numbers=TRUE,main="Within occupations and w


occ.maj.upperlower.rbg<-  lowerUpper(rbg.occ[c(10,25:28,57:61,82:87),c
corPlot(occ.maj.upperlower.rbg,numbers=TRUE,main="Between occupations
```

What about the factor structure of TAI between occupational groups.

R code

```
occ.f3.bg<- fa(rbg.occ[c(26:29,57:61,82:87),c(26:29,57:61,82:87)],3)

ov <- c(26:29,57:61,82:87)
occ.f3.bg <- fa(rbg.occ[ov,ov],3)
occ.f3.scores <- factor.scores(occ.mean100[,ov+1],occ.f3.bg)   #becaus
occ.names <- rownames(occ.f3.bg$scores$scores)
occ.names <-  substr(occ.names,1,15)

occ.f3.bg$scores <- occ.f3.scores
biplot(occ.f3.bg,labels=occ.names,choose=c(1,2),cuts=1.8)
biplot(occ.f3.bg,labels=occ.names,cuts=1.8)
biplot(occ.f3.bg,labels=occ.names,choose=c(1,3),cuts=1.8)
biplot(occ.f3.bg,labels=occ.names,choose=c(2,3),cuts=1.8)
```

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