Validating Cattell's Sixteen Personality Factor Model with Exploratory Factor Analysis

Abstract

As one of the first uses of factor analysis, Raymond Cattell's Sixteen Personality Factor model was a revolution in psychometrics, paving the way for contemporary personality measures such as the Big Five traits. However, more recent studies on Cattell's conclusions have cast doubt on the validity of such a model due to its irreproducibility. Using 163 questionnaire answers from 35,376 individuals, we used exploratory factor analysis techniques (developed by Cattell himself) to retrace Cattell's analysis and compared the results to validate his model. Within the analysis, we used maximum likelihood estimation to get factor loadings, chose 16 factors, and then used a promax rotation to differentiate the chosen factors. While many questions were categorized into the factors they were originally meant to measure, we noticed many of the same problems cited by previous researchers, namely the grouping of certain components into more general factors and the lack of significance to support others. Additionally, we also argue that many of the patterns we observed in our results might have arisen from participant bias in the data collection process itself, as test-takers may have responded based on what they thought the questions measured.

Background and significance

The Sixteen Personality Factor Questionnaire (16PF Questionnaire) is a popular self-reported personality test developed by Raymond B. Cattell, and has many practical important applications on working with human behaviors, ranging from clinical diagnosis to career counselor. In developing this test, Cattell used factor analysis to determine the underlying personality traits based on self-ratings on questions (Cattell & Mead, 2008). Even though Exploratory Factor Analysis (EFA) is a very popular technique for studying human behavior in general, it is often misused in psychological research (Fabrigar et al., 1999). In particular, replication of Cattell's methodology is met with mixed results: while Cattell and Mead (2008) claimed that these traits "have been confirmed in a wide range of independent studies", a number of other researchers have failed to verify the factors in numerous different studies (Fehringer, 2004). What makes replicating these analyses so difficult is the fact that the obtained results are easily influenced by necessary subjective decisions within the process of factor analysis. The main purpose of this paper is therefore to validate the 16PF Questionnaire using factor analysis on a new dataset.

Methods

Data collection

Data used in our analysis was obtained from an online personality test (Personality-testing.info). The dataset consists of 169 columns, the first 163 of which correspond to each question asked in the personality test. The other 6 columns are miscellaneous details about the person taking the test, which were not used in this study. Each of the 49,159 rows is an individual who took the test. The full list of 163 questions can be found in the codebook in the data file available online. Answers are coded in a Likert scale, going from 1 (strongly disagree) to 5 (strongly agree).

While the columns of questions were originally named and grouped into distinct categories representing Cattell's 16 factors, we were concerned with how this may introduce confirmation bias into our research. Therefore, to minimize bias, we blinded our analysis by randomly rearranging the 163 columns and renaming them sequentially.

We also removed observations with at least one missed question in our analyses and worked only with the 35,376 complete observations.

Analytic Methods

Exploratory factor analysis (EFA) is a method of identifying the underlying structure of the data, where we assume that our observable variables are not independent, and arises from the more fundamental latent variables, or factors. To quantify the relationship between variables and factors, loadings between each pair are calculated, which are the correlation coefficients associated between them. These numbers can be found using different techniques, the most common of which is maximum likelihood estimation. Other steps in EFA are factor selection and factor rotation, which respectively seeks to simplify and differentiate factors.

Firstly, we used maximum likelihood procedures to obtain a list of 163 components (possible factors), their loadings on each question, and their corresponding eigenvalues. In order to retain a smaller number of components which explains as much variability in the data as possible, we decided to retain 16 components, the same as the number of factors the test claims to measure. This is mainly motivated by the fact that we are only interested in validating these categories and not in uncovering new ones (for a more involved discussion of different variable selection techniques, see Appendix A)

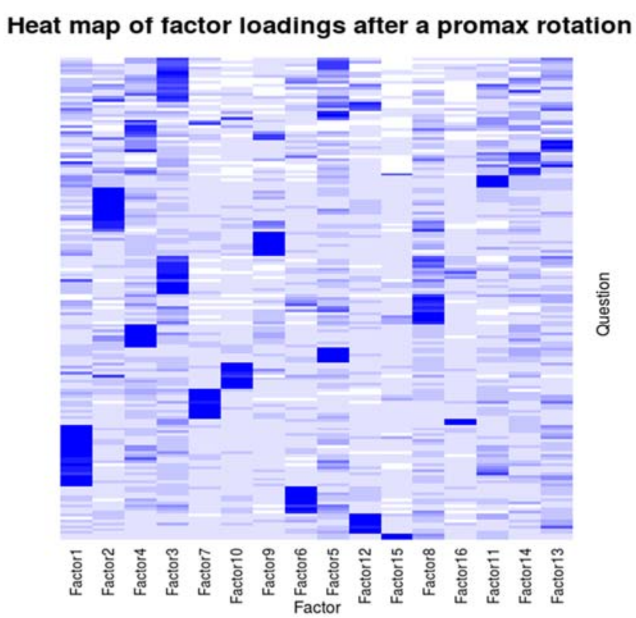
Next, we used factor rotation methods to distribute the variability explained across the chosen factors. This makes factors much more distinct from one another, helping with interpretation. Following Cattell's assumption that personality traits can be correlated with each other, we specifically looked at different oblique rotation methods. In the end, we decided to use a promax rotation, as it creates a loading matrix which best follows the guidelines of a simple structure (see Appendix B).

After obtaining our wanted factors, we reversed the blinding process, restoring each question their original labels. Then, we manually interpreted each factor, assigning them a label by the questions they are significantly[1] explained by.

Results

The heat map below shows each factor as a column and each question as a row, where darker colors represent more significant loadings. Therefore, the dark clusters of lines in each column shows the questions most correlated to that particular factor.

Each factor extracted was assigned a name based on the questions corresponding to its highest loadings, specifically by looking at the original categories these questions belonged to in the dataset. The assigned names and their corresponding personality factors in Cattell's original work are shown in the table below.



	Factor name as assigned in our analysis	**Labels assigned in Cattell's original work**	**Percent of total variation explained**
1	Anxiety	Emotional Stability	6%
		Apprehension	
2	Extraversion	Social Boldness	5%
		Liveliness	
3	Openness to experience	Openness to Change	4%
4	Warmth	Warmth	4%
5	Dominance	Dominance	3%
6	Rule Consciousness	Rule Consciousness	3%
7	Vigilance	Vigilance	3%
9	Self-reliance	Self-reliance	3%
8	Airheadedness[2]	Abstractedness	3%
15	Groundedness[2]		2%
10	Privateness	Privateness	2%
11	Irritableness	Tension	2%
13	Criticalness		2%
12	Perfectionism	Perfectionism	2%
14	Humor	(Liveliness)	2%
16	Love for Reading	(Sensitivity)	1%

[1] A factor-question loading is significant if its magnitude is greater than 0.5.
[2] These two factors are completely opposites: this is surprising, as this indicates that answers for "I like to daydream" and "I seldom daydream" are relatively independent from one another! This might suggest a problem with the questions themselves.

Discussion/Conclusions

The final factors corresponded remarkably well with the original, with a few key differences. Firstly, Emotional Stability and Apprehension now are grouped into a new factor we called Anxiety, while Social Boldness and Liveliness are also grouped together into Extraversion. Additionally, the trait Openness to Change also acquired a more specific sense of Openness to Experience by grouping together questions which ask about the person's willingness to discuss new ideas and be open to new experiences. Meanwhile, Cattell's original factor of Reasoning is entirely absent from our set of new factors.

This result brings up a few interesting observations, all of which confirms existing findings related to Cattell's model. Firstly, the new factors of Anxiety and Extraversion reflects what Cattell called Global Factors, which are five higher order traits encompassing the 16 primary factors. This reaffirms what other researchers have found while trying to replicate Cattell's methodology (Brown, 1971). Finally, it is also very interesting to see how Reasoning is not represented by our new set of personality traits, having been added by Cattell himself to represent general intelligence (Cattell and Mead, 2008).

However, it is very important to take into account the limitations and possible problems with this analyzing this data. Since a Likert scale was used to code responses, the process of data collection itself has potential bias. For example, people might change their responses depending on unconscious ideas of what is more socially acceptable. As mentioned in Method of Analysis, our specific choices regarding factor extraction and rotation were not the only valid options, and our results could have been very different had we chosen a different path. The factor matching process was quite subjective as we relied on our interpretation of the questions. Finally, it also very possible that test-takers were recognizing the redundant questions and answering correspondingly, possibly introducing bias to much of the patterns we see in our results.

Overall, our analysis yielded similar factors compared to Cattell's model, thus supports the validity of the 16PF Questionnaire. Due to limitations of our analysis as mentioned, further research should focus on the robustness of different factor extraction and rotation methods in different data sets, as well as the validity of the data itself.

References

Brown, J. (2009). “Choosing the Right Type of Rotation in PCA and EFA.” *JALT Testing & Evaluation SIG Newsletter, 3*(13), 20-25.

Cattell, H., & Mead, A. (2008). “The Sixteen Personality Factor Questionnaire (16PF).” *The SAGE Handbook of Personality Theory and Assessment: Volume 2 — Personality Measurement and Testing,* 135-159.

Fabrigar, L., Wegener, D., Maccallum, R., & Strahan, E. (1999). “Evaluating the use of exploratory factor analysis in psychological research.” *Psychological Methods, 4*(3), 272-299.

Fehringer, H. (2004). “Contributions and Limitations of Cattell's Sixteen Personality Factor Model.” Retrieved from http://www.personalityresearch.org/papers/fehringer.html

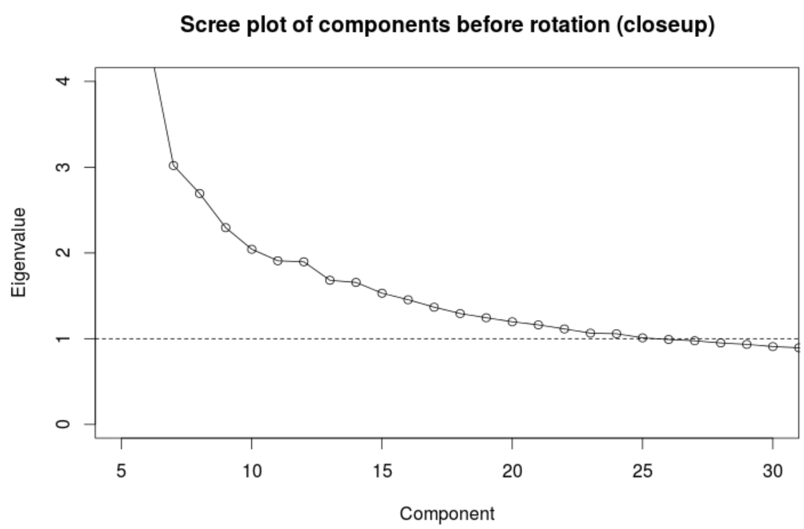
Personality-testing.info. (2014). Cattell's 16 Personality Factors Test [Data file and codebook]. Retrieved from http://personality-testing.info/_rawdata/.

Zwick, W.R. & Velicer, W.F. (1986). “Comparison of five rules for determining the number of components to retain.” *Psychological Bulletin*, 99, 432-442.

Appendix A: Factor Selection Criteria

In our study, we took three factor selection techniques into account: the scree plot, the Kaiser criterion, and parallel analysis. The simplest technique is simply to inspect a scree plot (shown below) for an elbow of where the eigenvalues start to level off, retaining all the factors to the left of said elbow. One criticism about this technique, however, comes from the fact that determining the location of the elbow is extremely subjective. The Kaiser criterion, also known as the eigenvalue-greater-than-one rule, suggests keeping all factors with eigenvalues greater than 1. However, this technique has been shown to have a tendency to overestimate the number of factors (Zwick & Velicer, 1986). Finally, parallel analysis is a technique by which the eigenvalues of null data are repeatedly simulated and compared with the observed eigenvalues, where factors are only retained if their observed eigenvalues are greater than the null eigenvalues.

In our study, while the Kaiser criterion suggested retaining 25 factors and parallel analysis suggested retaining 26, we felt that a smaller number of factors would be more appropriate, especially since a visual inspection of the scree plot shows a clear elbow between the 9th and 15th components. In the end, we decided to retain 16 factors because of the reasons stated above in the paper.



Appendix B: A Description of Simple Structure

A matrix exhibits **simple structure**, as defined by Louis Thurstone, if it satisfies the following:

1. Each variable should produce at least one zero loading on some factor.
2. Each factor should have at least as many zero loadings as there are factors.
3. Each pair of factors should have variables with significant loadings on one and zero loadings on the other.
4. Each pair of factors should have a large proportion of zero loadings on both factors (if there are say four or more factors total).
5. Each pair of factors should have only a few complex variables.

In other words, each factor in a matrix with simple structure will exhibit high factor loadings in a few variables while having zero loadings in the rest of the variables. This pattern of loadings should also be unique in order to differentiate it from other factors.

Appendix C: Code Used for Analysis

```
if( !require(magrittr) ) install.packages("magrittr")
library(magrittr)
if( !require(psych) ) install.packages("psych")
library(psych)
if( !require(GPArotation) ) install.packages("GPArotation")
library(GPArotation)

personality <- read.delim("personality.csv")

# Removes every row with at least one NA, retaining only complete cases
# Also retains only the columns we are interested in
personality[,1:163] %<>% inset(.==0, value = NA)
personality %<>% extract(personality %>% complete.cases %>% which, 1:163)

############################ BLINDING PROCEDURE ################################

# This code randomly orders the columns and assigns them new names
orig.cols <- colnames(personality)
random.seed <- sample(1:163)
personality %<>%
       extract(, random.seed) %>%
       set_colnames(1:163)

############################# FACTOR EXTRACTION ################################

# Compute the eigenvalues and eigenvectors
eigenvalues <- personality %>% cor %>% eigen %>% extract2("values")
eigenvectors <- personality %>% cor %>% eigen %>% extract2("vectors")

# Create a scree plot of the eigenvalues to determine the number of factors to retain
plot(1:163, eigenvalues, type = "o", main = "Scree plot of factors before rotation",
     xlab = "Component", ylab = "Eigenvalue")
abline(h = 1, lty = 2)

# Closeup of scree plot
plot(1:163, eigenvalues, type = "o",
     main = "Scree plot of components before rotation (closeup)",
     xlab = "Component", ylab = "Eigenvalue", xlim = c(5, 30), ylim = c(0, 4))
abline(h = 1, lty = 2)

# K-1 Criterion
eigenvalues %>% is_greater_than(1) %>% sum

# Parallel Analysis (WARNING: RESOURCE-INTENSIVE)
personality.pa <- personality.complete[,1:163] %>% cor %>% fa.parallel(n.obs = 35376)


############################### ROTATION ########################################

### Maximum Likelihood Factor Analysis with 16 factors ###

##### PROMAX ROTATION
promax.loadings <- factanal(personality.complete,
                           factors = 16, rotation = "promax") %>%
                    extract2("loadings")

# Print loadings in a pretty format
print(promax.loadings, digits = 2, cutoff = .3, sort = TRUE)
```

```
# Heat map of loadings
promax.loadings %>%
       abs %>%
       heatmap(main = "Heat map of factor loadings after a promax rotation",
               ylab = "Question", xlab = "Factor",
               col = colorRampPalette(c("white", "blue"))(10))

########################### UNBLINDING RESULTS #################################

# Putting labels back onto questions
rownames(promax.loadings) <- orig.cols[random.seed]
```