How important is the General Factor of Personality? A General Critique

William Revelle and Joshua Wilt
Northwestern University

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Is there a general factor of personality?

Fundamental questions in the assessment of cognitive and non-cognitive dimensions of personality are what is the appropriate number of factors/dimensions to extract from a data set and what is the structure of these factors. Hierarchical models have been used frequently in the cognitive domain (Carroll, 1993; Horn & Cattell, 1966, 1982) to reveal higher-order factors (e.g., g_c, g_f and g). In the non-cognitive domain, hierarchical models are employed less frequently, however, recent work has examined hierarchical models of anxiety (Zinbarg & Barlow, 1996; Zinbarg, Barlow, & Brown, 1997) and shows lower order factors as well as a higher order one. Few have applied this procedure to the entire domain of non-cognitive personality. Recently, Philippe Rushton and his colleagues (Rushton & Irwing, 2008; Rushton, Bons, & Hur, 2008; Rushton & Irwing, 2009) have done so. Extending Musek's initial finding of a one-factor solution in different inventories measuring the "Big 5" (Musek, 2007), the seemingly startling finding from Rushton's work is that there is indeed a higher order factor (the "General Factor of Personality") to be found in at least five major personality inventories. Their work is carefully done and does indeed show a general factor. But is this surprising or important? Perhaps, but only if we think that the higher order factor is as important as such general factors are in the intelligence domain or anxiety domain. We show that a) there are fundamental flaws in the analytical procedures used by Rushton and his colleagues; b) when correcting for these errors, the magnitude of a general factor of personality is about half of what is found in the cognitive domain; and c) the utility of a general factor is less than that of using lower level factors as predictors.

Multiple ways of evaluating the importance of a factor

There are at least four different ways to measure the importance of a factor or component in factor or components analysis. Each method may also be applied to examining the importance of a general factor. We first describe these methods and then apply them to simulated correlation matrices with known structures to determine which method best recovers the latent structure of each correlation matrix. We then apply these same techniques to five of the data sets reported by Rushton and his colleagues as well as three reported by Musek and then finally compare these results to several well known data sets of cognitive ability.

Method 1: Eigen Values

Consider a correlation matrix, $\mathbf{R}$, with a factor $\mathbf{\Lambda}$ with loadings λ_i and eigen value $\lambda = \mathbf{\Lambda}'\mathbf{\Lambda} = \sum \lambda_i^2$. The first measure of importance is a direct comparison of the magnitude of the factor's eigen values to the rank of the matrix[1]. For non-singular correlation matrices, the rank will be the number of variables and so this is just $\frac{\lambda}{N}$ where N is the number of variables. This ratio will indicate the amount of variance in the correlation matrix associated with that factor (or component). It is also an index of the average correlation between any two items (or tests) accounted for by that factor or component. Because the numerator and denominator will both increase with N, it is insensitive to the number of tests being analyzed. This is the approach of Musek (2007) and in at least one case, by Rushton and Irwing (2009).

Method 2: Correlations between Lower Order Factors

A second approach is to extract a higher order factor (or even sometimes, a higher order component) from the correlations between the lower order factors (or sometimes, the lower order components). In the case of just two lower order factors, loadings on this higher order factor are underdetermined and a typical solution is just to use the square root of the interfactor correlations. The importance of such a "general factor" is then interpreted in terms of its loadings on the lower order factors. This seems to be the approach favored by Rushton and his colleagues in some of their analyses.

Method 3: $\omega_{hierarchical}$ (ω_h)

The third method to estimate the importantance of general factor is to use the approach of McDonald (1999), Revelle and Zinbarg (2009) or Zinbarg, Revelle, Yovel, and Li (2005) and is the ratio of the sum of the correlations accounted for by the general factor divided by the sum of the original correlations. If $\mathbf{\Lambda}$ is a general factor of the set of variables, then

$$\omega_{hierarchical} = \omega_h = \frac{\mathbf{1'\Lambda\Lambda'1}}{\mathbf{1'R1}} = \frac{(\sum \lambda_i)^2}{\sum\sum R_{ij}}$$

may be thought of as the reliability due to the general factor of that set of variables. ω_h is the ratio of the sum of correlations reproduced by a factor to the sum of all correlations[2]. ω_h can be conceptualized briefly as examining the direct effect of the second or third order factor not on the lower order factors, but on the variables themselves (Holzinger & Swineford, 1937; Jensen & Weng, 1994; Reise, Morizot, & Hays, 2007; Schmid & Leiman, 1957). A general factor can be found either by Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis (CFA). When using EFA, lower order factors are allowed to correlate and a higher order (general) factor is found from these correlations. The

[1]In some of the papers and articles describing this work, there is an unfortunate confusion between components analysis and factor analysis. This is perhaps due to the interchangeable use of these very different terms by one of the major commercial software packages. Indeed, in that software program, the loadings matrix of a principal components analysis is incorrectly labeled as "factor loadings".

[2]Unfortunately (McDonald, 1999) introduces two "coefficients ω", one of which, ω_h or $\omega_{hierarchical}$ is a measure of the importance of a general factor. The other, ω_t or ω_{total} is a measure of the total reliability of a test.

loadings of this general factor on the variables are then found by using a Schmid Leiman transformation (Schmid & Leiman, 1957). An alternative technique for finding the general factor is to use CFA to directly find a *bifactor* solution. Hierarchical models are found merely by allowing the first order factors to correlate and then finding a second order factor to account for their correlations.

When estimating the parameters for either method 2 or 3, it is possible to use EFA or CFA. The seeming advantage of CFA is that goodness of fit statistics are available for the overall model. Various CFA fit statistics consider the size of the elements of the residual matrix ($\mathbf{R}^* = \mathbf{R} - \mathbf{\Lambda\Lambda}'$) for a hypothesized Λ matrix. Conceptually, all of these approaches consider the size of the squared residuals $\mathbf{R}^{*2}$ and either find the root means square of these residuals or sum the squared residuals divided by their standard error to find a χ^2. Other goodness fit indices derived from this χ^2 compare the magnitude of the residual χ^2 with the χ^2 of the original correlation matrix. All of these later set of approaches indicate whether the *overall* model fits the data, not whether a general factor is or is not necessary. Some of the analyses reported by Rushton and his colleagues use CFA and compare fits with and without a general factor. But such comparisons are asking no more than are the lower order factors themselves correlated.

Application of Eigen Values, ω_h, and Correlations between Lower-Order Factors to simulated Correlation Matrices

What is important to realize is that the simple question of what is the percentage of variance due to a general factor will have different answers depending upon which approach is used. We first apply Methods 1, 2, and 3 to eight example correlation matrices (S1-S8) with *equal average item intercorrelations* but differing in their general factor saturation. Each set is made up of two groups of items, with equal correlations within both groups but progressively smaller correlations between the groups. All eight example matrices have the same overall average inter-item correlation, .30. Sets S1 ... S4 are formed from two groups of size three with average correlations of .30, .45, .60 and .75 within groups, but with between group inter-item correlations of .3, .2, .1, and 0 respectively. Sets (S5 ... S8) have similar structures, also with an overall *average* correlation of .3, but for two groups of size 6 with within group correlations of .30, .42, .54, and .66 within groups and between group inter-item correlations of .3, .2, .1, or 0 between the first and last six tests.This is may be seen graphically in the first two rows of Figure 1. The shading within each box represents the magnitude of the correlations for that set. Thus, the diagonal (correlations of 1.0) are darkest, and equal levels of shading imply equal magnitude of the correlations.

It is clear by inspection that there is just one factor (a general factor) in sets S1 and S5, and two uncorrelated factors (no general factor) in sets S4 and S8. What is somewhat less clear is how much is the general factor saturation in sets S2, S3, S6 and S7. A number of different estimates of the general factor are listed in Table 1. The ratio of the first eigen value to the rank of the matrix for either a components solution (C_1/N) or a factor solution (Λ_1/N) (Method 1) is clearly not an indication of a general factor, for they are sensitive

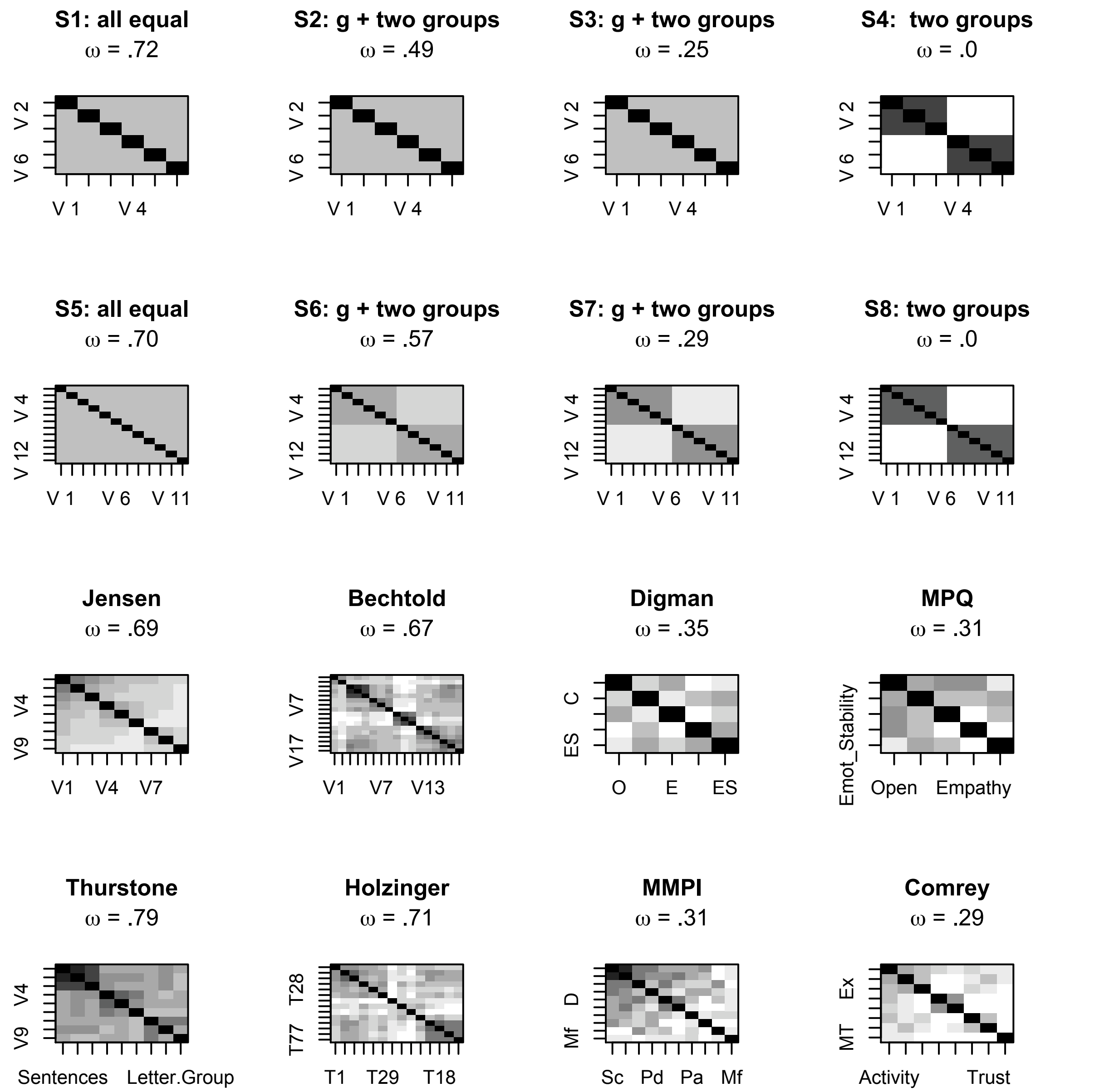


Figure 1. Examples of a general factor. Each figure graphically portrays a correlation matrix with shading representing the magnitude of the correlation. The diagonal is a correlation of 1. The first two rows show correlation matrices of 6 or 12 variables with just a general factor, a large general with two group factors, a small general and two groups, and just two group factors. The average intercorrelation of the items in the first and second row is .3 for all eight sets and thus $\alpha = .72$ for all sets in the first row and $\alpha = .84$ for all sets in the second row. The last two rows show seven real data sets and one simulated data set. Thurston, Bechtoldt and Holzinger are examples from the cognitive domain, Digman, MPQ, MMPI and Comrey are from Rushton and colleagues. Jensen is a prototypical general factor example. ω_h is found using EFA.

just to the average correlation and in the case of principal components, to the size of the data set. The correlation between the lower order factors (Method 2) either significantly over estimates (sets S1 and S5) or under estimates (sets S3 and S7) the *item* variance associated with a general factor. The square root of the correlation over estimates the general factor saturation for all the cases, except when the correlation between lower order factors is zero. ω_h and the ratio of the eigen value of the general factor to the rank of the matrix (Λ_g/N, Method 3), found by EFA using the `omega` function in the *psych* package (Revelle, 2009) in R (R Development Core Team, 2009)) are sensitive, as they should be, to the average between group correlation. For cases with a clear two group factor structure, ω_h is underdetermined and was found by the setting the two group factors to have equal loadings on the general factor (Zinbarg, Revelle, & Yovel, 2007).

Extending the analysis on the "General Factor of Personality"

The preceding analyses show that ω_h properly estimates the general factor saturation (McDonald, 1999; Revelle & Zinbarg, 2009) and suggest that Rushton's failure to use ω_h to estimate the general factor saturation in different personality inventories may have resulted in less than optimal solutions. Musek (2007) also did not use ω_h to evaluate the importance of a general factor. Our strategy in the remainder of the paper is to apply ω_h analyses to data sets in which a general factor has been reported. We then compare estimates of a general factor in personality to the general factor saturation found in classic cognitive ability data sets.

In addition to the example data sets, Table 1 shows estimates of the importance of a general factor emerging from an ω_h analysis for the data sets discussed below, and the last two rows of Figure 1 graphically represents the general factor in a selected sample of these data sets. Even a cursory analysis of the table and figure shows that a general factor is not as well-represented in personality (mean $\omega_h = .38$) as it is in cognitive ability (mean $\omega_h = .73$). Note that the means for analyses using Method 1 (comparing the magnitude of the first principal component or first factor to the rank of the matrix) do not differ between the Rushton and Musek analyses (means = .42 and .31) and the Cognitive measures (means = .44 and .39). Nor do they differ substantially when using Method 2 (the correlation between the subfactors), means = .31 and .41 for the Personality and Cognitive measures, respectively. However, when using the appropriate methodology for estimating a general factor (Method 3), there are substantial differences between the two content domains. The average magnitude of the size of the general factor divided by the rank of the matrix is more than twice as large in the cognitive domain (.33) than it is in the personality domain (.16). Converting these to estimates of ω_h lead to values of .73 and .38 for cognitive and personality measures, respectively.

Although the "Big 5" model of non-cognitive aspects of personality is partly credited to John Digman's influential chapter in the Annual Review (Digman, 1990), Digman also proposed a higher order structure of two super factors (Digman, 1997). As is clear from

Table 1: Alternative estimates of general factor saturation for the eight simulated data sets (S1:S8) in Figure 1, data sets in which the general factor of personality has been extracted, and classic cognitive ability data sets. *Method 1: The first Eigen Value from a principal components analysis or factor analysis divided by number of items* (N) equals the proportion of variance accounted for by that component or factor. C_1 is the eigen value of the first principal component, Λ_1 is the eigen value for the first factor found by minimal residual factor analysis. *Method 2: Correlation between group factors.* r_Λ is the correlation between the first and second group factors, or, in the case of the MMPI and ability items, the average of the between factor correlations. *Method 3: ω analyses.* Λ_g is the eigen value of the general factor found by a Schmid-Leiman transformation; ω_h is MacDonald's $\omega_{hierarchical}$. *R/M* is the estimate of GFP saturation appearing in empirical articles authored by Rushton and Musek. For Rushton's first four analyses, this is r_Λ emerging from structural equation modeling. For the MPQ, this is Λ_1/N. Each of Musek's estimates is C_1/N.

	Method 1		Method 2	Method 3			
	C_1/N	Λ_1/N	r_Λ	Λ_g/N	ω_h	R^2	*R/M*
S1	.42	.30	1.00	.30	.72	.72	
S2	.42	.30	.44	.20	.48	.48	
S3	.42	.30	.17	.10	.25	.25	
S4	.42	.37	.00	.00	.25	.25	
S5	.36	.30	1.00	.30	.84	.84	
S6	.36	.30	.48	.20	.56	.56	
S7	.36	.30	.19	.10	.28	.28	
S8	.36	.33	.00	.00	.00	.00	
Rushton's Analyses							
Digman's Medians	.40	.27	.33	.14	.35	.35	.45
Mount's Meta Analysis	.44	.31	.41	.17	.40	.37	.44
Comrey Scales	.29	.19	.26	.08	.27	.31	.41
MMPI	.39	.35	.15	.16	.37	.41	.49
MPQ	.46	.33	.25	.15	.31	.35	.33
Musek's Analyses							
Big Five Inventory	.50	.39	.38	.23	.50	.52	.50
IPIP	.42	.29	.30	.17	.40	.46	.40
Big Five Observer	.45	.32	.42	.20	.45	.45	.45
Cognitive Ability Data Sets							
Thurstone's 9	.54	.48	.55	.40	.74	.74	
Thurstone and Bechtoldt's 17	.37	.34	.29	.28	.72	.78	
Holzinger's 14	.37	.32	.29	.28	.71	.69	
Brigham and Thurstone's 9	.56	.51	.56	.49	.85	.89	
Holzinger and Harman's 24	.34	.31	.38	.22	.65	.66	
Means							
Rushton & Musek	.42	.31	.31	.16	.38	.40	.43
Cognitive Ability	.44	.39	.41	.33	.73	.75	

inspection of the correlation matrices of the Big 5 reviewed by Digman, the five factors are not orthogonal. In a meta-analysis of the Digman study, Rushton and Irwing (2008) have presented both median and weighted average correlation matrices. Rushton and Irwing (2008) used confirmatory procedures to extract a higher order general factor from these correlations.

An alternative solution, using the procedure of Schmid and Leiman (1957) is to calculate the g loadings from the hierarchical solution, extract the general factor, and the find the residual loadings on the remaining orthogonal factors (Figure 2). The amount of general factor saturation, McDonald's coefficient ω_h (McDonald, 1999; Revelle & Zinbarg, 2009; Zinbarg et al., 2005), is found by squaring the sum of the general factor loadings and dividing by the sum of the total correlation matrix. The resulting value, .35, is the percentage of variance accounted for by the general factor. Note that this is a smaller value than Rushton and Irwing (2008) obtained (.45) using the correlation between lower-order factors found through structural equation modeling to estimate the general factor saturation. This same analyses can be repeated on other data sets reported by Rushton and Irwing (2008) and Rushton and Irwing (2009).

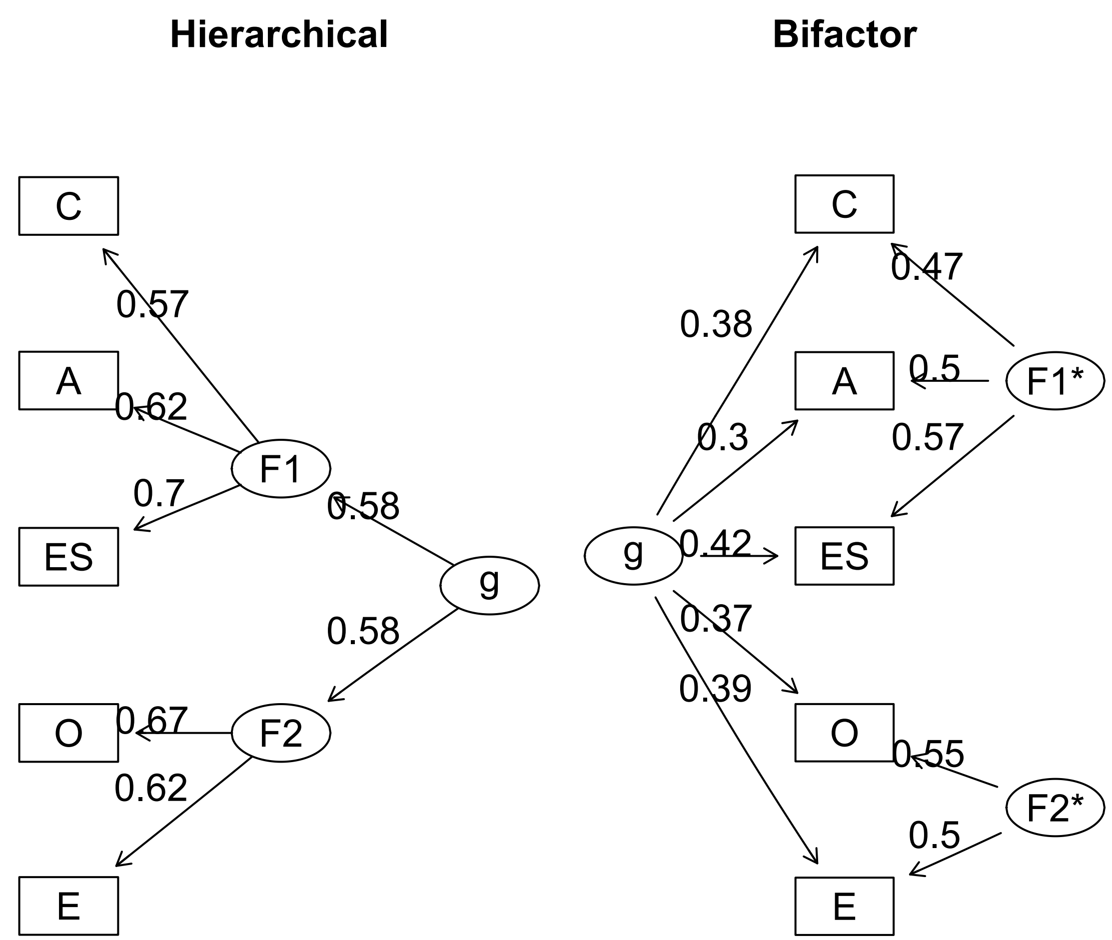
Mount et al.'s (2005) meta-analysis

Rushton and Irwing (2008) extracted a general factor from Mount, Barrick, Scullen, and Rounds (2005)'s meta-analytic results for Big 5 scale intercorrelations that were derived from four inventories assessing Big 5 content: the NEO-PI-R (Costa & McCrae, 1992); the Hogan Personality Inventory, HPI (Hogan & Hogan, 1995), the Personal Characteristics Inventory (Mount, Barrick, & Callans, 1999), and the International Personality Item Pool (Goldberg, 1999). Rushton and Irwing (2008)'s estimate of the general factor saturation, computed again by the correlation between lower-order factors emerging from structural equation modeling, was .44. This is slightly higher than MacDonald's ω_h, (.40).

The Comrey Personality Scales

The bi-factor solution for the Comrey Personality Scales (correlations taken from the 1995 manual) (Comrey, 1995, 2008), originally analyzed for a general factor in Rushton and Irwing (2009), is also given in Table 1. Once again, the low saturation of the general factor (ω_h = .27, compare with Rushton and Irwing (2009)'s estimate of 41% general factor saturation) combined with several low loadings of primary scales on the general factor suggest that the higher order factor alone may not provide an adequate description of the data. When examining the CFA solution to the Comrey (Rushton & Irwing, 2008, Figure 1) it is clear that their "general factor" is actually just a measure of what they label as "Extraversion" but could better be described as a blend of Activity, Emotional Stability, and Extraversion.

Figure 2. An example of an exploratory hierarchical solution versus a exploratory bifactor solution of the Digman median correlations. The exploratory procedure allows some small cross loadings between the two lower level factors and the tests. When using a confirmatory factor model for the hierarchical model, the loadings are .61, .56, and .72 for the first factor and .55 and .76 for the second factor with general factor loadings of .60. The confirmatory bifactor model produces general factor loadings of .44, .20, .48, .32 and .45 for C, A, ES, O, and E respectively. This leads to an ω_h value of .36. All analyses done using the *psych* and *sem* packages in R.



The MMPI

Yet another data set reported by Rushton and Irwing (2009) that shows the general factor is the MMPI-2 (Helmes, 2008). However, applying a bifactor analysis, this general factor accounts for 37% of the variance is the MMPI-2 scales (Table 1) rather than the 49% Rushton and Irwing (2009) found from the correlations between lower order factors. Additionally, various scales showed extremely low loadings on the general factor.

The Multicultural Personality Questionnaire

The last dataset that Rushton and Irwing (2009) reported a general factor for is the Multicultural Personality Questionnaire, MPQ (Zee & Van Oudenhoven, 2001). Rushton and Irwing (2009) used principal axis factoring to show that the general factor accounted for 33% of the common item variance, however, structural equation modeling suggested that a bifactor model provided a better fit than a general factor alone. Additionally, structural equation modeling showed that not all scales included in the MPQ loaded on the general factor. The general factor emerging from our exploratory bifactor analysis (Table 1) accounted for a similar 31% of the variance in the MPQ.

Re-analyzing Musek (2007)

Musek (2007) relied on the variance accounted for by the first principal component to estimate a general factor in three independent samples. Each sample was assessed with a different Big 5 assessment, translated into Slovenian: Sample 1 was assessed with the Big Five Inventory, BFI (John, Donahue, & Kentle, 1991), sample 2 the IPIP, and sample 3 the Big Five Observer, BFO (Caprara, Barbaranelli, & Borgogni, 1994). The proportion of scale variance in the Big 5 attributable to the general factor was .50 for the BFI, .40 for the IPIP, and .45 for the BFI. Although not recommended for reasons discussed earlier, Musek's first principal component analyses agree very well with the more appropriate ω_h calculation (Table 1).

Comparison to mental ability tests

We can compare these solutions of personality tests to what is found when analyzing some classic data sets. Five sets are considered: a) 9 mental tests from Thurstone (McDonald, 1999; Thurstone & Thurstone, 1941); b) 17 mental tests from Thurstone and Bechtoldt (Bechtoldt, 1961); c) 14 tests from Holzinger and Swineford (1937); d) 9 tests from Brigham (Thurstone, 1933) and e) 24 mental tests from Harman (1967). The first four data sets are included in the `bifactor` data set in the **psych** package. The last is in core R.

9 mental tests from Thurstone

A classic data set is the 9 variable Thurstone problem which is discussed in detail by R. P. McDonald (1985, 1999). These nine tests were grouped by Thurstone, 1941 (based on other data) into three factors: Verbal Comprehension, Word Fluency, and Reasoning. The original data came from Thurstone and Thurstone (1941) but were reanalyzed by Bechthold (1961) who broke the data set into two. McDonald, in turn, selected these nine variables from a larger set of 17. The general factor saturation of the 9 tests, estimated by ω_h, was .74.

17 mental tests from Thurstone/Bechtoldt

This set is the 17 variables from which the clear 3 factor solution used by McDonald (1999) is abstracted. ω_h, of these variables was .72.

14 mental tests from Holzinger

These 14 variables are from Holzinger and Swineford (1937) who introduced the bifactor model (one general factor and several group factors) for mental abilities. This is a nice demonstration data set of a hierarchical factor structure that can be analyzed using the omega function, $\omega_h = .71$.

9 mental tests from Brigham/Thurstone

These 9 mental tests reported by Thurstone (1933) are the data set of 4,175 students reported by Professor Brigham of Princeton to the College Entrance Examination Board. This set does not show a clear bifactor solution but still has a high general factor saturation, $\omega_h = .85$.

24 mental tests from Holzinger/Harman

The 24 mental tests from Holzinger and Swineford have been analzyed by Harman (1967) and many others as an example of factor analysis. ω_h, for these tests was .65.

It is clear from all five of these classic data sets that the general factor saturation of cognitive tests is much higher than the general factor saturation of non-cognitive measures.

Factor indeterminancy and the General Factor

Although factors are identified at the structural level, it is well known (but frequently ignored) that the factor model is not identified at the data level. That is, factor scores are typically *estimated* by regressing the factors against the observed variables. When this is done, it is possible to find the amount of factor variance accounted for by the original variables. This value, R^2, is a direct function of the inverse of the correlation matrix and the factor loadings. The greater the R^2, the more precisely the factor scores can be estimated. The minimum correlation between two such factor score estimates is $2R^2 - 1$ (Grice, 2001). That is, if $R^2 < .5$ then it is possible to find two estimates of the general factor that are themselves negatively correlated. Examining Table 1, it is clear that all but one of the GFP results have $R^2 < .5$ (mean = .40) while none of the ability measures suffer from this problem (mean = .75). It is difficult to think of any reason to consider such poorly defined measures as would allow a minimum correlation of -.2 between two estimates of the GFP.

Creating a general factor when it is not there

Although the current evidence for a general factor in the non-cognitive domain is lacking, this does not rule out the possibility that future investigations will discover a general factor in personality inventories that have yet to be examined. Any future investigation should take note of an additional concern relevant to extracting a general factor in the noncognitive domain that is not present when exploring the cognitive domain. Specifically, one of the primary differences between ability measures and non-cognitive personality measures is that ability measures are all positively correlated. That is, the probability of getting any one ability item correct is positively related to the probability of getting any other item correct. Jensen and Weng (1994) state that this should be a prerequisite for extracting a general factor from a data set. In contrast, within the personality domain, the direction of an item is taken as somewhat arbitrary ("I like to go to lively parties" is scored positively, but "I prefer reading to meeting people" is scored negatively, but both are seen as markers of extraversion). Even more important, the direction of the scale is arbitrary. Some inventories score for Neuroticism, others for Emotional Stability. Scales are scored for what is behaviorally important or what is socially valued. Neuroticism predicts the likelihood of psychiatric admissions and life long risk for a major depressive episode, while telling someone that they have a low emotional stability score is seen as nicer than saying they have a high neuroticism score. Unfortunately, taking advantage of this arbitrary direction and reverse scoring items can lead to what seems to be a general factor even when there is clearly not one.

Consider 24 simulated items representing a two dimensional circumplex structure in which there is no general factor. By reverse keying items half of the items, a structure that had 0% general factor by construction is now estimated to have an ω_h of .75.

A similar problem occurs when we analyze the correlation matrix of the NEO-PI-R Costa and McCrae (1992). The general factor of the NEO facets allowing for reversal scoring is .49, while without item reversals it is .12! This is mainly due to the fact that the NEO scores for Neuroticism rather than Emotional Stability. Reverse scoring the Neuroticism facets to become Emotional Stability leads to an ω_h of .45. Repeating this analysis at the correlational structure of the five factors of the NEO leads to ω_h of the five factors of .28 when Neuroticism is allowed to be reversed keyed, and .12 when it is not.

Discussion and conclusions

Yes, it is possible to find a general factor of personality. But is this the most useful level of analysis? We do not believe so. Based upon the psychometric principal that a measure should be interpreted in terms of its common variance, it is hard to justify the conclusion that Rushton advocates, namely thinking about measures when less than half of the variance is associated with that construct. Considering the problem of factor indeterminancy, it is even harder to think that a factor which can have two negatively correlated estimates has any psychological value.

We have previously considered the hierarchical structure of personality inventories and suggested that items or tests should be combined as long as an internal consistency estimate (β (Revelle, 1979) which is similar to ω_h (Zinbarg et al., 2005)) increases for the combined scale. Applying this logic to the examples from the cognitive domain results in one, high level scale. But applying the same algorithm to the personality inventories discussed above does not. Rather, the β estimates for the lower level constructs are greater than when they are combined.

Just as some have claimed that affect reflects one common dimension from happy to sad (Russell & Carroll, 1999), others have shown that it is better to consider happy and sad as separate dimensions (Rafaeli & Revelle, 2006). This debate between forming higher order constructs versus focusing on lower order, but correlated constructs is long running. In the field of intelligence, the introduction of the bifactor model (Holzinger & Swineford, 1937) clarified the use of hierarchical models and allowed for the estimation of the relative importance of each. When g has large saturations on each test, it is clearly useful to think in terms of g. But when the saturation is low, and when there is good biological evidence for separate, although correlated systems associated with the lower order constructs (e.g., the three brain systems model of reinforcement sensitivity theory (Corr, 2008; Gray & McNaughton, 2000; Revelle, 2008)), it will prove more useful to develop theories at the lower order level.

When we compare the general factor solutions of the personality tests to those of the ability tests, it is apparent that what is a clear g in ability is much muddier in personality.

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