

# Using unidim rather than omega in estimating unidimensionality

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A simple index of the unidimensionality of a scale,  $u$ , is introduced.  $u$  is just the product of two other indices:  $\tau$  (a measure of  $\tau$  equivalence) and  $\rho_c$  (a measure of congeneric fit). Simulations of  $u$  across scales ranging from 3 to 24 items with various levels of factor homogeneity, and demonstrations of its performance on 45 different personality and ability measures are shown. Comparisons with traditional measures (e.g.,  $\omega_h$ ,  $\alpha$ ,  $\omega_t$ ) show greater sensitivity to unidimensional structure and less sensitivity to the number of items in a scale.  $u$  is easily calculated with open source statistical packages and is relatively robust to sample sizes ranging from 100 to 5,000.

## Public Significance

How to evaluate whether a psychological scale measures just one construct is a recurring problem in assessment. We present an intuitively easy to understand and easily calculated new index of unidimensionality,  $u$ . We compare this index to conventional measures with simulated and real data sets.

Evaluating the dimensionality of a measure has been an ongoing challenging for many years. If a multi-item scale is unidimensional, scores on that scale will reflect one underlying construct. If not, then scores reflect the underlying construct as well as other, extraneous sources of variance.

To understand the challenge, consider a multi-item scale designed to measure a single construct (T) with inevitable random error (E). That is, each item  $x_i$  contributes construct-specific variance and random error to the scale score. This may be represented as

$$x_i = \lambda_i \tau + \epsilon_i \quad (1)$$

with variances

$$\sigma_i^2 = \lambda_i^2 \sigma_\tau^2 + \sigma_\epsilon^2 \quad (2)$$

If  $\lambda$  is equal for all items and the variances of the  $\epsilon$  are all equal, the items are said to be *parallel*. That is, all items contribute equally with respect to the construct measured by the scale. Similarly, subsets of the items from the scale would represent *parallel forms*. If  $\lambda$  is equal for all items but the variances of the  $\epsilon$  are unequal, the items are said to be  *$\tau$  equivalent*. If the  $\lambda$  are unequal (as is the typical case for most measures used in psychology), the items are said to be *congeneric*. For parallel

items, all the correlations and covariances among items will be identical. For  $\tau$  equivalent items, the covariances will be identical but the correlations will not. For congeneric items, neither the covariances nor the correlations need to be identical.

The relationships among these values are often used to evaluate the internal consistency of scales as an estimate of reliability as with, for example, Cronbach's  $\alpha$  (aka Guttman's  $\lambda_3$ ). For a scale ( $X$ ) that is scored as the sum of its items ( $X = \sum x_i$ ), internal consistency reliability is estimated as the proportion of construct-specific variance to total observed variance. That is,

$$\rho_{xx} = \frac{\sigma_\tau^2}{\sigma_X^2}$$

Although frequently used,  $\alpha$  is a particularly poor measure of whether the test is unidimensional because it assumes the case of  $\tau$  equivalence (Cronbach, 1951). In other words, the items are presumed to have the same (true score) relationship to the measured construct. This means  $\alpha$  is just a function of the number of items ( $k$ ) and the average covariance of the items:

$$\alpha = \frac{\sigma_X^2 - \sum \sigma_i^2 + k\bar{\sigma}_{ij}}{\sigma_X^2} = \frac{k}{k-1} \frac{k\bar{\sigma}_{ij}}{(\sigma_i^2 + (k-1)\bar{\sigma}_{ij})} \quad (3)$$

An alternative to  $\alpha$  is omega-total ( $\omega_t$ ). Based upon a factorial model of the item covariances (McDonald, 1999),  $\omega_t$  is found by replacing the item variances ( $\sigma_i^2$ ) with the amount of common variance ( $h^2$ ) for each item:

$$\omega_t = \frac{\sigma_X^2 - \sum \sigma_i^2 + \sum h_i^2}{\sigma_X^2}. \quad (4)$$

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Importantly,  $\omega_t$  reflects the total amount of common variance among the items rather than the amount due to any single factor or dimension, and this limits its usefulness as a measure of unidimensionality. The difficulty is that  $\omega_t$  does not indicate the extent to which items co-vary on underlying dimensions beyond the primary or “general” factor.

McDonald (1999) also introduced another coefficient which he also referred to as  $\omega$  but which Zinbarg, Revelle, Yovel, & Li (2005) refer to as hierarchical  $\omega$  ( $\omega_h$ ).  $\omega_h$  may be found by a hierarchical factoring of the original data followed by a subsequent Schmid-Leiman Transformation (Schmid & Leiman, 1957) or by a bifactor solution with a general factor and a number of group factors. In both cases,  $\omega_h$  is found by summing the loadings on the general factor and comparing the square of their sum to the test variance:

$$\omega_h = \frac{(\sum \lambda_i)^2}{\sigma_x^2} \quad (5)$$

As  $\omega_h$  represents the proportion of general factor variance to total test variance, it directly addresses the difficulty introduced by using  $\omega_t$  (the proportion of all common variance to total test variance) as an estimate of unidimensionality. In cases where one or more subset(s) of items share group variance that is not fully explained by variance on the general factor among all items,  $\omega_h$  will be a smaller proportion than  $\omega_t$  and a much better estimate of unidimensionality.

Although Revelle & Condon (2019) have previously recommended reporting  $\omega_h$ ,  $\alpha$ , and  $\omega_t$  for all scales in order to test for unidimensionality unfortunately  $\omega_h$  is not appropriate for very short scales. This is because  $\omega_h$  requires at least 2 (and preferably  $\geq 3$ ) lower level factors in order to find a hierarchical solution. Since the degrees of freedom for a factor model with  $k$  factors and  $n$  variables is:

$$\frac{n(n-1)}{2} - nk + \frac{k(k-1)}{2}$$

the minimum number of variables needed for a 2 factor model to be defined is 5. Note that this case does not allow for a proper hierarchical solution for  $\omega_h$ , as this requires 3 lower level factors. The minimum number of variables needed to properly estimate a hierarchical solution is 6.

Here we introduce a very simple alternative test for unidimensionality —  $u$ , which may be found using the `unidim` function in the *psych* package in R — and examine its properties using both simulated and real data.

### Unidim: a test for unidimensionality

The logic is deceptively simple: Unidimensionality implies that a one factor model of the data fits the covari-

ances of the data. If this is the case, then the factor model implies that  $R = FF' + U^2$  will have residuals of 0. Similarly, this also implies that the observed correlations will equal the model. Thus, the sum of the observed correlations (with the diagonal replaced by the communalities) should match those of the factor model. Compare these two models:  $R - U^2$  versus  $FF'$ . This is the  $\rho_c$  estimate.

$$\rho_c = \frac{\sum FF'}{\sum (R - U^2)} = \frac{\mathbf{1}FF'\mathbf{1}'}{\mathbf{1}(R - U^2)\mathbf{1}'}, \quad (6)$$

where  $\mathbf{1}$  is just a vector of 1s.  $\rho_c$  is basically a test of whether a congeneric model fits.

This works well, but when some of the loadings are very small, it is probably not a good idea to think of the items as forming a unidimensional scale. Thus, an alternative model (the  $\tau$  statistic) compares the observed correlations ( $r_{ij}$ ) to the mean correlation ( $\bar{r}$ ) and considers 1 - the ratio of the sum of the squared residuals to the sum of the squared correlations

$$\tau = 1 - \frac{\sum_{i \neq j} (r_{ij} - \bar{r}_{ij})^2}{\sum_{i \neq j} r_{ij}^2} \quad (7)$$

$\tau$  will achieve a maximum if the item covariances are all identical (a tau equivalent model).

The product of  $\rho_c$  and  $\tau$  is the measure of unidimensionality,  $u$ . That is, congeneric fit x tau equivalent fit as a measure of unidimensionality. In the following tables, we show how  $u$  behaves in various simulations as well as with real data. We also show the behavior of the  $u$  statistic as a function of sample size and compare the standard errors as a function of sample sizes (Figure 1). These demonstrations use the functions `unidim` and `omega` as implemented in the *psych* package (Revelle, 2023b) for the open source statistical system R (R Core Team, 2023). Output from both functions is also shown in the `reliability` function<sup>3</sup>.

### Tests with simulations

To demonstrate the `unidim` function, we simulate a four factor model for 12, 24, 48 and 96 items with loadings as specified in Table 1. We use the `sim` and `sim.minor` functions to generate the data. Both functions generate a latent variable model by multiplying the factor loading matrix by a matrix of random normal deviates and then adding error. `sim.minor` follows the advice of MacCallum & Tucker (1991) who distinguished between the factor model we want (pure factors) and a generating model of pure factors with a number of smaller, nuisance factors. The first four columns of

<sup>3</sup>`reliability` was modified in *psych.2.3.10* to incorporate  $\omega_h$  estimates for models with less than 4 variables.

Table 1 show loadings on four factors. The first set (column 1) contain large (.7, .6, .5), the second medium (.6, .5, .4) and the third small (.5, .4, .3) loadings. The fourth column shows mixed loadings of .7, .5, and .3. The final four columns were used when generating minor factors, with loadings of  $\pm .2$  randomly assigned to variables.

Data were generated for 500 simulated subjects using both the “pure” (just the first four factors) and the noisy (all 8 factors) model. Solutions for 3, 6, 12, and 24 items per scale for 500 simulated participants for pure factors are shown in Table 2 and four noisy data in Table 3. The last four rows reflect scales formed from the first and second factors for 6, 10, 12, and 24 items<sup>4</sup>. These are clearly not unidimensional. Several things to note in these tables: Following the Spearman-Brown equation,  $\alpha$  and  $\omega_t$  increase with the number of items in the scale. Neither statistic flags the scales formed from two orthogonal factors as poor fits. Because a hierarchical model is not identified for three item scales,  $\omega_h$  was forced to a one factor solution for those scales but properly identifies the last four scales as having low values for general factor saturation. The behavior of the  $u$  statistic is very gratifying, in that it seems not to increase with the number of items per scale, and correctly identifies the last four scales as non-unidimensional. This is in striking contrast to  $\omega_t$  or  $\alpha$  which show very “reasonable” values for these non-unidimensional scales.

### Applying unidim to real data

We show the utility of the unidim statistic on three data sets available in the *psychTools* package (Revelle, 2023a) for the R statistical system. The first, the ability data set includes 16 items for 1525 participants from the International Cognitive Ability Resource (Condon & Revelle, 2014) which represents 4 lower level factors and one higher level factor (Table 4 part 1). The items are dichotomous. The second represents five scales of five items each from the bfi data set for 2,800 participants. The 25 Likert-like items had six response choices and represent five personality factors (Table 4 part 2). The third set are 135 items from the SAPA Personality Inventory (Condon, 2018) for 4,000 participants and are available as the spi dataset; these also had six response options (“very inaccurate” to “very accurate”) (Table 5).

Although normally scored as five separate constructs, for demonstration purposes we formed composite scales formed from two (E+O), three (A+C+N) or five (all) constructs. This is a particularly nice example of the advantage of the  $u$  statistic as contrasted with the more conventional  $\alpha$  and  $\omega_t$  statistics. For the later show quite reasonable values (.71 - .84) for scales that are not unidimensional.  $u$  and  $\omega_h$  on the the hand, show clear evidence (.30 - .41) for multidimensionality (Table 4 part 3).

### Sensitivity to sample size

For practical purposes, we addressed the question of the effect of sample size on the  $u$  statistic. We simulated 100, 500, 1,000 and 5,000 participants using the factor structure shown in Table 1. For each simulation we performed 100 replications. We also examined the effect of sample size on  $\omega_t$ . It is quite clear (Figure 1) that even for samples as small as 100, the  $u$  statistic could distinguish between unidimensional scales versus multidimensional scales. The pattern of results show that  $u$  is, in contrast to  $\omega_t$ , not sensitive to the number of items in the scale, but is sensitive to unidimensionality. (Compare the first 16 to the last four columns of each panel.)

<sup>4</sup>Because we also are finding split half estimates, we limited our examples to 24 items to allow for finding all split half values from the 1,352,078 possible splits.

**Table 1**

The simulated loadings matrix. Rows 1-12 were repeated 8 times to generate the 96 item loadings. The loadings represent large, medium and small loadings, as well as a mixed set. The minor factors had loadings of  $\pm 0.2$  for four nuisance factors.

Variable	Large	Medium	Small	Mixed	m1	m2	m3	m4
V1	0.7	0.0	0.0	0.0	0.0	0.0	0.2	-0.2
V2	0.6	0.0	0.0	0.0	0.0	0.2	0.0	0.0
V3	0.5	0.0	0.0	0.0	-0.2	0.0	0.0	0.2
V4	0.0	0.6	0.0	0.0	0.2	0.2	0.2	0.2
V5	0.0	0.5	0.0	0.0	0.0	-0.2	0.0	0.0
V6	0.0	0.4	0.0	0.0	0.0	0.2	0.0	0.2
V7	0.0	0.0	0.5	0.0	0.2	0.2	0.0	0.0
V8	0.0	0.0	0.4	0.0	-0.2	0.0	-0.2	0.2
V9	0.0	0.0	0.3	0.0	0.0	0.2	0.0	0.2
V10	0.0	0.0	0.0	0.7	-0.2	0.0	0.2	0.0
V11	0.0	0.0	0.0	0.5	0.0	0.0	0.2	-0.2
V12	0.0	0.0	0.0	0.3	-0.2	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...
V85	0.7	0.0	0.0	0.0	0.0	0.0	0.2	0.0
V86	0.6	0.0	0.0	0.0	0.0	0.0	0.0	-0.2
V87	0.5	0.0	0.0	0.0	0.2	0.2	0.0	0.0
V88	0.0	0.6	0.0	0.0	-0.2	0.2	0.0	0.0
V89	0.0	0.5	0.0	0.0	-0.2	0.0	0.0	0.2
V90	0.0	0.4	0.0	0.0	0.2	0.0	-0.2	-0.2
V91	0.0	0.0	0.5	0.0	0.0	0.0	0.2	-0.2
V92	0.0	0.0	0.4	0.0	-0.2	0.0	0.0	0.0
V93	0.0	0.0	0.3	0.0	0.2	-0.2	0.2	0.0
V94	0.0	0.0	0.0	0.7	0.0	0.2	0.2	0.0
V95	0.0	0.0	0.0	0.5	0.0	0.2	0.0	0.0
V96	0.0	0.0	0.0	0.3	0.0	0.0	-0.2	0.2

**Table 2**

Various estimates of unidimensionality and reliability for 500 simulated participants for scales formed from 3, 6, 12, and 24 items with factor loadings as specified in Table 1. The last four rows report results for scales formed from two orthogonal subscales.  $u$  is the unidimensional statistic,  $\tau$  and  $\rho_C$  are the  $\tau$  and congeneric fits,  $\omega_h$  and  $\omega_l$  are the two omega statistics,  $\alpha$  is the traditional estimate. Max split and min split represent the maximum and minimum split half reliabilities found by complete sampling of all  $C_{k/2}^k$  possible split half coefficients.  $\bar{r}$  reports the mean correlation in the scale. Median  $r$  is just the median value.

Variable	$u$	$\tau$	$\rho_C$	$\omega_h$	$\alpha$	$\omega_l$	Max split	Min split	$\bar{r}$	Median $r$	N items
high.3	0.99	0.99	1.00	0.61	0.61	0.61	0.58	0.53	0.34	0.36	3
med.3	0.99	0.99	1.00	0.54	0.54	0.54	0.50	0.47	0.28	0.28	3
low.3	0.97	0.97	1.00	0.34	0.33	0.34	0.32	0.30	0.14	0.14	3
mixed.3	0.92	0.92	1.00	0.45	0.44	0.45	0.44	0.41	0.21	0.18	3
high.6	0.96	0.96	0.99	0.77	0.76	0.77	0.78	0.73	0.35	0.33	6
med.6	0.91	0.92	0.99	0.68	0.67	0.68	0.70	0.65	0.26	0.26	6
low.6	0.85	0.88	0.97	0.53	0.52	0.53	0.56	0.47	0.15	0.15	6
mixed.6	0.73	0.74	0.98	0.64	0.61	0.63	0.66	0.55	0.21	0.18	6
high.12	0.94	0.95	0.99	0.87	0.87	0.87	0.89	0.84	0.35	0.35	12
med.12	0.88	0.90	0.98	0.79	0.78	0.79	0.82	0.75	0.23	0.23	12
low.12	0.78	0.83	0.94	0.67	0.66	0.67	0.71	0.57	0.14	0.14	12
mixed.12	0.77	0.78	0.98	0.79	0.77	0.78	0.82	0.71	0.22	0.20	12
high.24	0.95	0.95	1.00	0.93	0.93	0.93	0.95	0.91	0.36	0.35	24
med.24	0.90	0.92	0.98	0.88	0.88	0.88	0.91	0.84	0.23	0.23	24
low.24	0.81	0.85	0.95	0.82	0.82	0.82	0.87	0.75	0.16	0.16	24
mixed.24	0.78	0.79	0.98	0.89	0.88	0.89	0.92	0.80	0.24	0.21	24
F2.6	0.32	0.50	0.63	0.43	0.50	0.52	0.59	0.12	0.14	0.07	6
F2.10	0.30	0.49	0.62	0.49	0.66	0.67	0.75	0.09	0.16	0.06	10
F2.12	0.12	0.19	0.63	0.59	0.62	0.60	0.73	0.09	0.12	0.05	12
F2.24	0.23	0.34	0.68	0.67	0.79	0.79	0.88	0.12	0.14	0.07	24

**Table 3**

Various estimates of unidimensionality and reliability for 500 simulated participants for scales formed from 3, 6, 12, and 24 items with major and minor factor loadings as specified in Table 1. The last four rows report results for scales formed from two orthogonal subscales. Column headings are the same as in Table 2. The addition of small amount of noise makes very little difference (compare with Table 2).

Variable	$u$	$\tau$	$\rho_c$	$\omega_h$	$\alpha$	$\omega_t$	Max split	Min split	$\bar{r}$	Median r	N items
high.3	0.98	0.98	1.00	0.69	0.68	0.69	0.66	0.60	0.42	0.43	3
med.3	0.99	0.99	1.00	0.57	0.57	0.57	0.54	0.47	0.31	0.31	3
low.3	0.73	0.73	1.00	0.29	0.26	0.29	0.29	0.13	0.10	0.07	3
mixed.3	0.93	0.93	1.00	0.50	0.49	0.50	0.49	0.46	0.24	0.21	3
high.6	0.97	0.97	1.00	0.80	0.80	0.80	0.82	0.75	0.39	0.38	6
med.6	0.94	0.95	0.99	0.71	0.70	0.71	0.73	0.67	0.28	0.26	6
low.6	0.82	0.86	0.95	0.50	0.50	0.51	0.55	0.42	0.14	0.13	6
mixed.6	0.77	0.79	0.97	0.68	0.66	0.68	0.71	0.59	0.25	0.21	6
high.12	0.96	0.97	0.99	0.87	0.87	0.87	0.90	0.83	0.36	0.35	12
med.12	0.92	0.94	0.98	0.82	0.82	0.82	0.86	0.78	0.27	0.27	12
low.12	0.82	0.87	0.95	0.72	0.72	0.72	0.78	0.63	0.17	0.17	12
mixed.12	0.77	0.78	0.98	0.81	0.80	0.81	0.83	0.75	0.25	0.22	12
high.24	0.94	0.96	0.99	0.93	0.93	0.93	0.95	0.89	0.35	0.35	24
med.24	0.90	0.92	0.98	0.90	0.90	0.90	0.93	0.84	0.26	0.26	24
low.24	0.83	0.88	0.95	0.83	0.83	0.83	0.88	0.75	0.17	0.17	24
mixed.24	0.76	0.78	0.97	0.89	0.89	0.89	0.93	0.81	0.25	0.22	24
F2.6	0.28	0.43	0.65	0.42	0.52	0.56	0.61	0.06	0.15	0.06	6
F2.10	0.12	0.20	0.61	0.55	0.55	0.60	0.71	0.04	0.11	0.04	10
F2.12	0.17	0.27	0.64	0.56	0.63	0.66	0.76	0.08	0.12	0.05	12
F2.24	0.12	0.20	0.62	0.73	0.73	0.76	0.85	0.14	0.10	0.05	24

## Summary and Conclusion

The problem of assessing the unidimensionality of a scale has been a challenge for many years, and many solutions have been offered. Here we have suggested a simple index,  $u$  which is the the product of indices of  $\tau$  equivalence and  $\rho_c$  or congeneric equivalence.  $u$  is simple to calculate (e.g., the `unidim` or `reliability` functions in the `psych` package for R). We compare the  $u$  index to two popular indices of scale quality,  $\omega_h$  and  $\omega_t$ , showing that  $u$  is insensitive to the number of items in a scale and is robust across sample sizes from 100 to 5000.

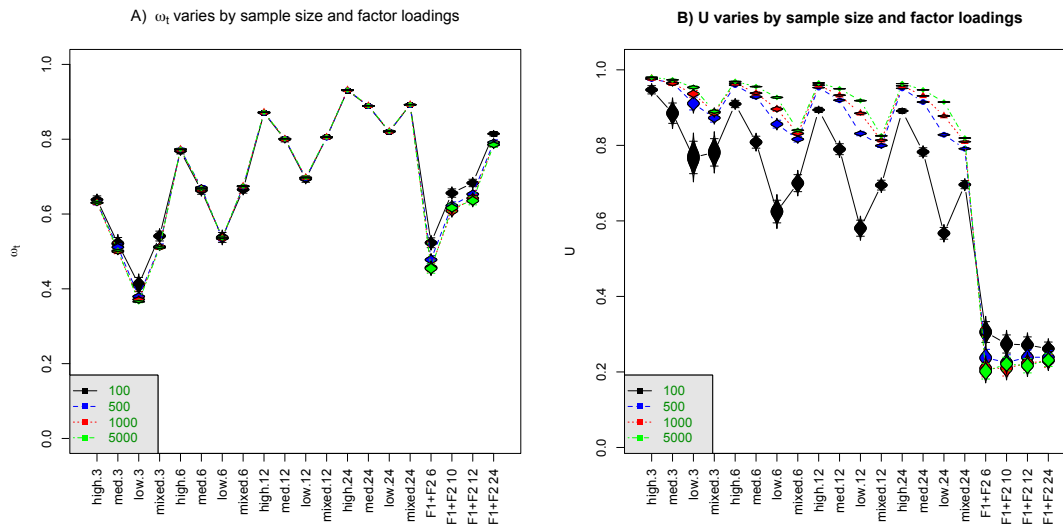
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**Table 4**

Multiple reliability measures for the **ability** data set with 16 items and 1,525 participants and the **bfi** data set with 2,800 participants for 25 items. The first three columns report **unidim** statistics  $u$ ,  $\tau$ , and  $\rho_c$ , the next three columns the conventional  $\omega_h$ ,  $\alpha$ , and  $\omega_t$  internal consistency estimates, the next are based upon a split half decomposition of the scales and report the maximum and minimum split half reliabilities. The last three columns show the mean and median within scale correlations followed by the number of items per scale. The ICAR16 represents a higher order factor composed of four lower level factors. Although the **bfi** is scored as five unidimensional constructs, the last three lines represent scales formed from two (E+O), three (A+C+N) or five (all) constructs. For the latter three scales, note how the high value of  $\alpha$  and  $\omega_t$  conflict with low values of  $u$  and  $\omega_h$  which are better indicators of unidimensionality.

Variable	$u$	$\tau$	$\rho_c$	$\omega_h$	$\alpha$	$\omega_t$	Max split	Min split	$\bar{r}$	Median r	N items
ICAR dataset											
ICAR16	0.84	0.91	0.93	0.56	0.83	0.85	0.87	0.73	0.23	0.21	16
reasoning	0.98	0.98	1.00	0.05	0.65	0.65	0.65	0.64	0.31	0.31	4
letters	0.99	0.99	1.00	0.65	0.67	0.68	0.68	0.66	0.34	0.33	4
matrix	0.92	0.94	0.98	0.37	0.54	0.59	0.58	0.49	0.23	0.22	4
rotate	0.99	0.99	1.00	0.71	0.77	0.78	0.78	0.74	0.45	0.44	4
bfi dataset: single construct scales											
extraversion	0.97	0.97	0.99	0.55	0.76	0.82	0.78	0.71	0.39	0.38	5
openness	0.85	0.88	0.97	0.39	0.61	0.70	0.66	0.53	0.24	0.23	5
agree	0.89	0.90	0.99	0.64	0.71	0.75	0.75	0.62	0.33	0.34	5
conscientious	0.95	0.97	0.98	0.53	0.73	0.77	0.73	0.64	0.35	0.34	5
neuroticism	0.93	0.95	0.98	0.71	0.81	0.85	0.83	0.73	0.47	0.41	5
bfi multi construct scales											
E+O	0.48	0.60	0.81	0.36	0.71	0.77	0.79	0.38	0.20	0.21	10
A+C+N	0.41	0.61	0.67	0.33	0.78	0.81	0.86	0.48	0.19	0.14	15
all	0.37	0.55	0.67	0.30	0.82	0.84	0.90	0.51	0.15	0.13	25

**Figure 1**

The  $\omega_t$  and  $u$  statistics behave very differently across the number of items per factor and sample size. Panel A shows how  $\omega_t$  increases with the number of items/factor and varies by the size of the factor loadings. It is relatively insensitive to the non-unidimensionality of scales formed from multiple factors and to sample size. Panel B shows how the  $u$  statistic does not increase with the number of items per scale, is sensitive to the size of the factor loadings, and is very sensitive to the non-unidimensionality (the four right hand observations in both panels). Sample sizes range from 100 (black) to 500, 1000, and 5000 simulated participants. Catseyes display standard deviations of 100 replications for each sample size.



**Table 5**

Multiple reliability measures of the *spi*-135 (Condon, 2018). The SAPA Personality Inventory (Condon, 2018) has five higher order scales assessing the “Big Five” and 27 lower level scales assessing other aspects of personality. The Big 5 measures have 14 items each and the 27 lower level measures have 5 items each. The *spi* data set in the *psychTools* has 4,000 observations on these 135 items plus 10 criteria/demographic variables. The columns are the same as in Table 4.

Variable	$u$	$\tau$	$\rho_c$	$\omega_h$	$\alpha$	$\omega_t$	Max split	Min split	$\bar{r}$	Median r	N items
Agree	0.69	0.80	0.86	0.55	0.87	0.89	0.91	0.66	0.32	0.25	14
Consc	0.75	0.84	0.90	0.58	0.86	0.88	0.91	0.70	0.30	0.27	14
Neuro	0.84	0.90	0.94	0.61	0.90	0.92	0.94	0.75	0.40	0.36	14
Extra	0.82	0.89	0.92	0.66	0.89	0.91	0.94	0.77	0.38	0.34	14
Open	0.68	0.77	0.88	0.47	0.84	0.86	0.89	0.62	0.27	0.22	14
Compassion	0.99	0.99	1.00	0.80	0.88	0.89	0.87	0.82	0.59	0.58	5
Trust	0.99	0.99	1.00	0.80	0.87	0.89	0.87	0.83	0.58	0.58	5
Honesty	0.96	0.97	0.99	0.71	0.81	0.84	0.83	0.76	0.46	0.46	5
Conservatism	0.82	0.90	0.91	0.56	0.78	0.85	0.84	0.61	0.41	0.35	5
Authoritarianism	0.89	0.93	0.95	0.63	0.81	0.86	0.85	0.73	0.46	0.46	5
EasyGoingness	0.90	0.92	0.98	0.45	0.68	0.76	0.73	0.63	0.29	0.29	5
Perfectionism	0.82	0.83	0.99	0.34	0.70	0.74	0.72	0.66	0.31	0.33	5
Order	0.92	0.94	0.99	0.62	0.81	0.85	0.82	0.76	0.46	0.42	5
Industry	0.99	0.99	1.00	0.72	0.84	0.86	0.84	0.80	0.52	0.50	5
Impulsivity	0.98	0.98	1.00	0.72	0.87	0.90	0.87	0.82	0.58	0.58	5
SelfControl	0.90	0.94	0.96	0.49	0.76	0.83	0.80	0.68	0.39	0.36	5
EmotionalStability	0.98	0.98	1.00	0.65	0.85	0.89	0.84	0.81	0.52	0.50	5
Anxiety	0.99	0.99	1.00	0.83	0.90	0.91	0.89	0.85	0.64	0.62	5
Irritability	0.98	0.99	0.99	0.78	0.89	0.91	0.89	0.83	0.61	0.60	5
WellBeing	0.99	0.99	1.00	0.80	0.90	0.92	0.90	0.85	0.63	0.63	5
EmotionalExpressiveness	0.92	0.93	0.99	0.73	0.80	0.83	0.83	0.73	0.45	0.43	5
Sociability	0.97	0.98	0.99	0.66	0.85	0.89	0.85	0.79	0.53	0.50	5
Adaptability	0.92	0.93	0.99	0.62	0.80	0.84	0.82	0.76	0.44	0.42	5
Charisma	0.94	0.96	0.98	0.67	0.82	0.86	0.84	0.73	0.47	0.43	5
Humor	0.91	0.92	0.99	0.68	0.78	0.82	0.81	0.76	0.42	0.40	5
AttentionSeeking	0.92	0.93	0.99	0.80	0.88	0.90	0.89	0.81	0.58	0.67	5
SensationSeeking	0.97	0.98	0.99	0.77	0.86	0.89	0.87	0.79	0.55	0.54	5
Conformity	0.89	0.93	0.96	0.67	0.82	0.87	0.85	0.67	0.47	0.47	5
Introspection	0.92	0.93	0.99	0.56	0.78	0.84	0.81	0.74	0.41	0.41	5
ArtAppreciation	0.89	0.90	0.99	0.68	0.80	0.83	0.81	0.77	0.44	0.46	5
Creativity	0.97	0.97	1.00	0.70	0.85	0.86	0.85	0.81	0.52	0.53	5
Intellect	0.99	0.99	1.00	0.81	0.86	0.87	0.84	0.83	0.54	0.52	5

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