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ACQUIESCENT RESPONDING IN BALANCED MULTIDIMENSIONAL SCALES AND EXPLORATORY FACTOR ANALYSIS

URBANO LORENZO-SEVA

ROVIRA I VIRGILI UNIVERSITY

ANTONI RODRÍGUEZ-FORNELLS

INSTITUCIÓ CATALANA DE RECERCA I ESTUDIS AVANÇATS AND UNIVERSITY OF BARCELONA

Personality tests often consist of a set of dichotomous or Likert items. These response formats are known to be susceptible to an agreeing-response bias called acquiescence. The common assumption in balanced scales is that the sum of appropriately reversed responses should be reasonably free of acquiescence. However, inter-item correlation (or covariance) matrices can still be affected by the presence of variance due to acquiescence. To analyse these correlation matrices, we propose a method that is based on an unrestricted factor analysis and can be applied to multidimensional scales. This method obtains a factor solution in which acquiescence response variance is isolated in an independent factor. It is therefore possible, without the potentially confounding effect of acquiescence, to: (a) examine the dominant factors related to content latent variables; and (b) estimate participants' factor scores on content latent variables. This method, which is illustrated by two empirical data examples, has proved to be useful for improving the simplicity of the factor structure.

Key words: Acquiescence, balanced scales, exploratory factor analysis, factor simplicity.

Personality tests often consist of a set of Likert items in which respondents are asked to express how strongly they agree or disagree with a statement. This response format (as well as the dichotomous response format) is prone to an agreeing-response bias called acquiescence. Some authors consider the acquiescence response tendency to be a source of undesirable variance that must be suppressed (e.g., Hofstee, ten Berge, & Hendriks, 1998). Others (e.g., Billiet & McClendon, 2000) consider it to be a consistent style related to personality traits.

If we wish to control or minimize variance due to acquiescence, a method must be envisaged when the inventory is designed. One method is to use balanced scales. In a balanced scale, half of the items are worded in the opposite direction to the other half with respect to a general trait (or construct). If a test aims to measure more than one trait (i.e. it is multidimensional), the items related to each subscale must be balanced. This kind of scale has already proved to be useful in substantive research (Lentz, 1938; Ray, 1983; Hofstee et al., 1998; Billiet & McClendon, 2000).

The common assumption in balanced scales is that acquiescence responses to items in one direction will be balanced by acquiescence responses to items in the opposite direction. As a result, the sum of appropriately reversed responses should be reasonably free of acquiescence (Ray, 1983; Hofstee et al., 1998). However, the inter-item correlation matrix can still be affected by the presence of variance due to acquiescence (Bentler, 1969; Ray, 1983). If the correlation

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Requests for reprints should be sent to Urbano Lorenzo-Seva, Universitat Rovira i Virgili, Facultat de Psicologia, Ctra. de Valls s/n, 43007 Tarragona, Spain. E-mail: uls@urv.net

matrix is factor analysed, the corresponding factor solution will be disturbed by the presence of this variance (Ferrando, Lorenzo-Seva, & Chico, 2003). In addition, factor scores will also be affected by acquiescence response variance.

ten Berge (1999) proposed a principal component-based method for removing the acquiescent source of variation from the data. Essentially, this method consists of:

1. determining an 'acquiescence' component;
2. partialling this component; and
3. carrying out principal component analysis on the residual covariance matrix.

This method aims to examine the dominant components without the potentially confounding effect of acquiescence. Ferrando et al. (2003) extended ten Berge's principal component-based approach to an unrestricted factor-analytic approach. In this case, the method is limited to situations in which a theoretically unidimensional scale is analysed but the analyses suggest that the data are essentially bidimensional. They also proposed criteria that help to assess the plausibility of a bidimensional factor model in which one main factor is due to content variance (i.e. a factor related to the trait measured) and a second minor factor is due to acquiescence variance.

In this paper we extend Ferrando et al.'s method so that it can be used to analyse a balanced scale that is assumed to be multidimensional. First, we will briefly review ten Berge's (1999) and Ferrando et al.'s (2003) methods. Then we will present the new method in detail. Finally, we will illustrate the usefulness of the new method with two illustrative examples.

1. ten Berge's Principal Component-Based Method (1999)

ten Berge's method is based on principal component analysis and aims to remove the acquiescent source of variation from the correlation (covariance) matrix.

Let matrix $\mathbf{X}$ of order $n \times m$ hold the raw scores of n subjects on m items. The m items are an even set of items expected to be related to r latent content variables ($r < m$). In addition, each subset of items related to the same content variable must be balanced between positively and negatively phrased items. If $\mathbf{R}$ is the correlation (covariance) matrix of order $m \times m$, then the vector

$$\mathbf{a} = \mathbf{R}1\left(\mathbf{1}'\mathbf{R1}\right)^{-1/2} \tag{1}$$

is the vector of correlations between the variables and their mean. Values of $\mathbf{a}$ show how much each variable is affected by acquiescence. To remove the acquiescence from the correlation matrix $\mathbf{R}$, we can partial vector $\mathbf{a}$ to obtain the residual matrix

$$\mathbf{R}^* = (\mathbf{R} - \mathbf{aa}'). \tag{2}$$

Principal component analysis can be applied to the residual matrix $\mathbf{R}^*$ to obtain the loadings on the r content components. For example, when $\mathbf{R}^*$ has the eigendecomposition

$$\mathbf{R}^* = \mathbf{K}\Lambda\mathbf{K}', \tag{3}$$

with $\mathbf{K}$ an orthonormal $m \times m$ matrix and Λ diagonal with elements $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m$, then the $m \times r$ matrix of loadings $\mathbf{A}$ is obtained as

$$\mathbf{A} = \mathbf{K}_r\boldsymbol{\Lambda}_r^{1/2}, \tag{4}$$

where $\mathbf{K}_r$ contains the first r columns of $\mathbf{K}$ and Λ_r is the upper left submatrix of Λ of order $r \times r$. Finally, the loading matrix $\mathbf{A}$ can be rotated to show factor simplicity (Kaiser, 1974) by any orthogonal or oblique rotation method. If $\mathbf{T}$ is an $r \times r$ transformation matrix, the final pattern matrix related to content components is obtained by

$$\mathbf{C} = \mathbf{AT}, \tag{5}$$

while the correlation matrix between content component scores is obtained as

$$\Phi = \mathbf{T}^{-1}\mathbf{T}^{-1'}. \tag{6}$$

If $\mathbf{T}$ is orthonormal (i.e. the product $\mathbf{T'T}$ is an identity matrix), the component scores remain uncorrelated and $\mathbf{\Phi}$ is also an identity matrix. This is the case for the orthogonal rotation of matrix $\mathbf{A}$ when, for example, Varimax rotation is applied (Kaiser, 1958).

After ten Berge's method is applied, $\mathbf{C}$ is the rotated pattern matrix when variance due to acquiescence is removed. How acquiescence response affects each item is described by the values of vector $\mathbf{a}$. Note that the values in $\mathbf{a}$ will usually range from 0 to 1. A value of zero for a particular item would mean that participants' responses to the corresponding item are completely free of acquiescence. A value of one, on the other hand, would mean exactly the opposite. Note that $\mathbf{a'a}$ that is the total amount of variance explained by acquiescence.

The key reason for removing variance due to acquiescent response is that it may make it easier to interpret the content components. Clearly, the smaller the variance explained by acquiescence, the less impact its removal will have. The more variance the acquiescence explains, the better the chances are that removing it from the content components will be useful.

2. Ferrando et al.'s Method for Unidimensional Scales (2003)

Ferrando et al.'s method is an extension of ten Berge's but is based on unrestricted factor analysis of unidimensional content scales. In this case, the m items in matrix $\mathbf{X}$ are expected to be related to only one latent content variable (i.e. $r = 1$). Again, the items must be balanced between positively and negatively phrased items. If $\mathbf{R}$ is the correlation (covariance) matrix of order $m \times m$, it can be analysed by any method of factor analysis. However, Minimum Rank Factor Analysis (ten Berge & Kiers, 1991; also see ten Berge & Sočan, 2004) is adopted because it can distinguish the explained common variance from the total common variance, thus making it possible to assess more precisely the proportions of common variance explained by the supposed content and acquiescence factors. So, a loading matrix $\mathbf{L}$ of order $m \times 2$ is obtained such that

$$\mathbf{R} = \mathbf{LL'} + \mathbf{MM'} + \mathbf{\Psi}^2, \tag{7}$$

where $\mathbf{M}$ holds the loadings on those common factors that are discarded in the rank-2 solution and Ψ is a diagonal matrix containing the unique-factor standard deviations. To obtain the loadings on the content and the acquiescence factors, $\mathbf{L}$ is orthogonally rotated to a partially specified target and the values of one of the columns of the target matrix are fixed, while the values of the other column are left free. The values of the fixed column in the target are the corresponding correlations between the items and the sums of the standardized item scores. So, the fixed column is in fact the vector $\mathbf{a}$ in expression (1). This rotation may be resolved by the rotation for maximizing the congruence coefficient (Korth & Tucker, 1976). If $\mathbf{U}$ is the corresponding transformation matrix of order 2×2, the final loading matrix is obtained by

$$(\mathbf{b}_1|\mathbf{b}_2) = \mathbf{LU}, \tag{8}$$

where $\mathbf{b}_1$ and $\mathbf{b}_2$ are vectors containing the loading values of items on acquiescence and content factors, respectively.

3. Method for Multidimensional Scales

The method we propose is an extension of the two previous ones. It aims:

(a) to examine the dominant factors related to content latent variables; and
(b) to estimate participants' factor scores on content latent variables—in both cases without the potentially confounding effect of acquiescence.

The method is based on unrestricted factor analysis and the extension, with respect to Ferrando et al.'s method, is that the scale can be multidimensional (i.e. the value of r is greater than 1).

The first step is to obtain matrices $\mathbf{L}$ and Ψ in expression (7), where $\mathbf{L}$ is of order $m \times (r+1)$. So, the correlation matrix (or covariance) $\mathbf{R}$ must also be analysed by any method of factor analysis (note that Minimum Rank Factor Analysis is again recommended). Next, the possibility of rotating a matrix $\mathbf{W}$ is used to identify the column related to acquiescence factor. One column of $\mathbf{W}$ must maximize the congruence with $\mathbf{a}$, so it is determined by the method of Korth & Tucker (1976). Let $\mathbf{d}$ and $\mathbf{w}$ be vectors defined as

$$\mathbf{d} = \left(\mathbf{L}'\mathbf{L}\right)^{-1}\mathbf{L}'\mathbf{a} \tag{9}$$

and

$$\mathbf{w} = \mathbf{d}(\mathbf{d}'\mathbf{d})^{-1/2}. \tag{10}$$

Given the eigendecomposition of the matrix

$$\mathbf{I} - \mathbf{w}\mathbf{w}' = \mathbf{W}\Delta\mathbf{W}' \tag{11}$$

with $\mathbf{I}$ an identity matrix, $\mathbf{W}$ an orthonormal matrix of order $(r+1)\times(r+1)$, and Δ diagonal with elements $\delta_1 \geq \delta_2 \geq \cdots \geq \delta_r \geq \delta_{r+1} = 0$, the product

$$\mathbf{L}\mathbf{W} = (\mathbf{S}_r |\ \mathbf{s}) \tag{12}$$

leads to a matrix whose last column $\mathbf{s}$ contains the loading values of items on the acquiescence factor and $\mathbf{S}_r$ is an $m \times r$ matrix that can be rotated to show factor simplicity by any orthogonal or oblique rotation method. Whereas in the $r = 1$ case the last column of $\mathbf{U}$ is determined up to sign, we now have r columns of $\mathbf{W}$ that are determined up to an arbitrary orthogonal rotation.

If $\mathbf{T}_r$ is an $r \times r$ rotation matrix, the rotated pattern matrix related to content factors is obtained by

$$\mathbf{P}_r = \mathbf{S}_r\mathbf{T}_r, \tag{13}$$

while the correlation matrix between factor scores is obtained by

$$\Phi_r = \mathbf{T}_r^{-1}\mathbf{T}_r^{-1'}. \tag{14}$$

Note that, if factor scores are to be obtained, the overall loading matrix is $(\mathbf{P}_r |\ \mathbf{s})$, and the interfactor correlation matrix is

$$\begin{pmatrix} \Phi_r & \mathbf{0} \\ \mathbf{0}' & 1 \end{pmatrix} \tag{15}$$

where $\mathbf{0}$ is a vector of zeros. Once the factor solution is available, content and acquiescence factor scores can be obtained using any available procedure, such as the one proposed by ten Berge, Krijnen, Wansbeek, and Shapiro (1999). Note that content factor scores will be free of the potentially confounding effect of acquiescence.

4. First Illustrative Example

We illustrate these procedures by analysing the Five-Factor Personality Inventory (FFPI) adapted for Spanish by Rodríguez-Fornells, Lorenzo-Seva, and Andrés-Pueyo (2001). This is a Dutch questionnaire developed to assess the Big-Five model of Personality (Hendriks, Hofstee, & De Raad, 1999). The FFPI consists of 100 Likert-type items rated on a 5-point scale. The FFPI assesses a person's scores on the following content dimensions: *Extraversion*, *Agreeableness*, *Conscientiousness*, *Emotional Stability* and *Autonomy*. Each dimension is measured by 20 balanced items. The FFPI is therefore a balanced questionnaire designed so that variance due to acquiescence response can be removed. The above component-based approach has been used to analyse this inventory (Hendriks et al., 1999; Rodríguez-Fornells et al., 2001; Hendriks et al., 2003).

A reduced version of the FFPI was administered to a sample of 139 preuniversity students (86 women and 53 men). This consisted of 20 items, so each dimension in the inventory was measured by four balanced items. As we were interested in latent variables rather than components, ten Berge's component-based approach was not appropriate. Also, the method proposed by Ferrando et al. is meant to analyse unidimensional tests, while the inventory has five dimensions. This is therefore a situation in which our method is the most appropriate.

We analysed the inter-item Pearson correlation matrix by Minimum Rank Factor Analysis to obtain $\mathbf{L}$, computed vector $\mathbf{a}$ defined in expression (1), and obtained $(\mathbf{S}_r \mid \mathbf{s})$ by the orthogonal congruence rotation described in expression (12). To obtain content loading matrix $\mathbf{P}_r$, we used orthogonal Varimax rotation (Kaiser, 1958). For the purposes of comparison, we also analysed data using ten Berge's method based on principal component analysis. We computed loading matrix $\mathbf{C}$ by orthogonal Varimax rotation of $\mathbf{A}$ defined in expression (4).

Table 1 shows vectors $\mathbf{a}$ and $\mathbf{s}$. Note that the loading coefficients in $\mathbf{s}$ were not equal, which indicates that not all the items were equally affected by acquiescent responding. As expected, the congruence between vectors $\mathbf{a}$ and $\mathbf{s}$ was high (0.975), and the values of $\mathbf{a}$ tended to be systematically higher than the factor loadings in $\mathbf{s}$. The explained common variance of $\mathbf{s}$ was lower than that of $\mathbf{a}$, even though the proportion of explained common variance was higher for $\mathbf{s}$ than for $\mathbf{a}$ (as this proportion is related to the common variance).

Table 2 shows loading values on the five content factors. To help interpret this table, the items which measure in one direction are labelled 'P' (positive), and the items that measure in the opposite direction are labelled 'N' (negative). Also, the loading of each item expected to show the largest value is printed in bold. Our results agree with the theoretical expectations—except for items 2 and 5, that showed the largest loading in a position different than the one expected.

The total amount of variance explained by content factors was 8.095 (64.65% of the common variance) and the acquiescence factor explained 1.334 (10.66% of the common variance).

We have also used ten Berge's component-based approach to analyse the inter-item Pearson correlation matrix. Table 3 shows the loading values on the five content components. We computed Bentler's (1977) and Lorenzo-Seva's (2003) factor simplicity indices. Note that the indices were computed only for the five content factors and components shown in tables 2 and 3, respectively. Bentler's index was 0.906 and 0.832 for factor and component loading matrices, respectively. This meant that the former was simpler to interpret than the latter. Lorenzo-Seva's index supported this conclusion: values were 0.394 and 0.373 for factors and components, respectively.

The greater simplicity of the factor solution can be intuitively understood by studying the loading matrices in tables 2 and 3. Kaiser (1974) defined factor simplicity as the simplest possible solution in which each variable is generated by a single factor. This definition is related to the complexity of variables, which is usually defined by the number of salient loadings of each variable. For example, when a variable has loadings that are different from zero in only one factor and zero in the others, this variable is said to be of complexity one. If we consider that a salient

TABLE 1.
Acquiescence estimations for the 20 items.

Items	**a**	**s**
1	.307	.243
2	.165	.089
3	.331	.338
4	.306	.232
5	.274	.154
6	.147	.171
7	.338	.422
8	.184	.100
9	.113	.032
10	.272	.190
11	.431	.365
12	.276	.258
13	.209	.117
14	.428	.438
15	.350	.332
16	.320	.317
17	.224	.106
18	.170	.101
19	.268	.247
20	.345	.350
Explained variance	1.639	1.334
%	8.20	10.66

loading must show an absolute value larger than 0.25, then the loading matrix in table 2 has 12 variables of complexity one. The same criterion applied to the loading matrix in table 3 shows that only 8 variables are of complexity one. Note that each factor, or component, was expected to be defined by only 4 variables, so the difference in the number of variables of complexity one seems substantial.

Finally, we again analysed the inter-item Pearson correlation matrix using the classical approach: we extracted the r factors (without separating variance due to acquiescence) and rotated the loading matrix using orthogonal Varimax rotation. Bentler's and Lorenzo-Seva's simplicity indices reported values of 0.836 and 0.359, respectively. Both values were lower than when the variance due to acquiescent response was removed using our factor-based approach (0.906 and 0.394). This meant that removing the variance due to acquiescent responding gave a simpler factor structure.

5. Second Illustrative Example

The Spanish version of the FFPI was validated using a sample of 567 undergraduate college students (480 women and 87 men) enrolled on an introductory course of Psychology at the University of Barcelona (Rodríguez-Fornells et al., 2001). We reanalysed the data from this Spanish adaptation of the inventory using our factor-based approach. The comparison between the factor and the component approach with this data set is interesting because, given the number of items and dimensions of this particular situation, the component and factor approaches should provide similar results (Bentler & Kano, 1990).

TABLE 2.
Factor loading matrix obtained in the first illustrative example.

Items	Extraversion	Agreeableness	Conscientiousness	Emotional stability	Autonomy
1P	**.568**	.239	.095	.057	.072
2P	−.280	.068	**.307**	.251	−.336
3P	.120	.139	−.073	**.542**	−.139
4P	.276	**.370**	.267	.136	−.027
5P	−.011	.088	.204	.389	**.219**
6N	**−.733**	.225	.156	−.043	−.030
7P	.052	**.398**	.327	.051	.339
8N	.092	−.108	**−.503**	−.335	.054
9N	−.056	−.056	−.125	**−.762**	−.119
10P	.098	.152	−.063	.297	**.502**
11P	**.386**	.041	−.053	.119	.198
12P	.037	.023	**.668**	−.015	.036
13N	−.237	−.399	−.029	**−.524**	.073
14N	.146	**−.425**	−.334	−.169	.229
15N	−.020	−.181	.032	−.186	**−.284**
16N	.079	−.107	**−.725**	−.087	−.019
17P	.006	−.033	.097	**.572**	−.057
18N	**−.496**	.027	−.100	−.299	.069
19N	−.001	.071	−.058	.048	**−.656**
20N	.107	**−.812**	−.055	−.066	−.023
Explained variance	1.544	1.526	1.739	2.098	1.188
%	12.34	12.19	13.90	16.76	9.49

Note: Loading values that were expected to be the largest for each item are printed in bold.

With this data set, the components explained more raw variance, while the proportion of common variance was larger for the factors. However, no important differences were observed between solutions: congruence between **a** and the acquiescence factor was 0.996 and congruence between content components and content factors was greater than or equal to 0.999. Lorenzo-Seva's index showed that the factor simplicities of the two solutions were similar (0.396 and 0.397 for components and factors, respectively). Values for congruence and factor simplicity therefore showed that both solutions were virtually the same.

The total amount of raw variance explained by content factors and the acquiescence factor was 33.312 (42.06% of common variance) and 5.673 (7.16% of common variance), respectively.

6. Discussion

Balanced scales are designed to control or minimize the effect of acquiescent response variance. However, inter-item correlation matrices of such scales must be analysed by specific methods. Our method is an extension of two previous ones. ten Berge (1999) proposed a component-based method that first removes acquiescence response variance and then extracts content components. Ferrando et al. (2003) extended this method to unrestricted factor analysis of content unidimendional scales. We now have extended the method further using unrestricted factor analysis of content multidimendional scales.

TABLE 3.
Component loading matrix obtained in the first illustrative example.

Items	Extraversion	Agreeableness	Conscientiousness	Emotional stability	Autonomy
1P	**.588**	.377	.034	−.003	.065
2P	−.347	.086	**.347**	.307	−.383
3P	.142	.178	−.133	**.602**	−.147
4P	.297	**.620**	.218	.051	−.061
5P	−.092	.123	.217	.429	**.322**
6N	**−.690**	.253	.133	−.074	−.075
7P	.043	**.460**	.305	.000	.341
8N	.076	−.092	**−.614**	−.375	.027
9N	−.137	−.061	−.147	**−.752**	−.148
10P	.042	.136	−.088	.308	**.648**
11P	**.434**	.046	−.051	.100	.239
12P	.058	.013	**.754**	−.030	.053
13N	−.223	−.421	.016	**−.569**	.022
14N	.203	**−.503**	−.289	−.175	.212
15N	.042	−.298	.135	−.178	**−.358**
16N	.051	−.193	**−.725**	−.054	−.011
17P	−.023	−.096	.123	**.687**	−.026
18N	**−.658**	−.064	−.089	−.274	.098
19N	−.017	.102	−.109	.113	**−.744**
20N	.209	**−.665**	−.038	−.115	−.073
Explained variance	1.851	1.911	1.986	2.421	1.646
%	9.26	9.56	9.93	12.11	8.23

Note: Loading values that were expected to be the largest for each item are printed in bold.

In general, component and factor analyses produce congruent solutions when the same data set is analysed. However, when the number of measured variables is low compared to the number of latent variables, component analysis is not an adequate approximation of common factor analysis. The first illustrative example showed that in such a situation our method performs as expected, while ten Berge's (1999) component-based method is not fully suitable. When the number of measured variables is large compared to the number of latent variables, component and factor analysis produce not only congruent but even identical outcomes (Bentler & Kano, 1990). The second illustrative example showed that in such a situation our factor solution is similar to the component solution. Actually, the researcher should decide between ten Berge's approach and ours, depending on the purpose of the analysis:

(a) if component structure is meant to be analysed, then ten Berge's component-based method should be applied; and
(b) if factor structure is meant to be analysed, then our factor-based method should be applied.

Differences in the internal procedures related to each method are more technical than substantive.

In our method, the loadings on the acquiescence factor are not constrained to be equal. Different loading values would indicate that not all the items were equally affected by acquiescent response. This approach was also used by Ferrando et al. (2003). On the other hand, Billiet & McClendon (2000) suggested a restricted factor analysis model in which the loadings for all of the items on the acquiescence factor had to be equal. This equal specification is unrealistic in most cases. Although fit was acceptable in the model proposed by Billiet & McClendon (2000), which consisted of eight items and two content factors, modification indices suggested that the items were affected differently by acquiescence response.

Our method shares a limitation with Ferrando et al.'s method. This is the assumption that acquiescence and content are uncorrelated. However, this allows the content factor scores to be free of acquiescence response variance. This property of factor scores, which is not satisfied in direct scores, can be useful in applied research. In addition, if the aim is to measure participants' acquiescence response, the acquiescence factor scores can be used.

Hofstee (1994) proposed that mean scores for balanced subsets of items can be used to measure acquiescence, when the total set of items is unbalanced. Although Hofstee considered subtracting rather partialling acquiescence, the very idea that acquiescence can be removed even if only a subset of items are balanced offers an important extension of the range of applications for the methods discussed in this paper.

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