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Testing the generality of the general factor of personality: An exploratory bifactor approach

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Abstract

Objective: To investigate whether the psychometric properties of the general factor of personality (GFP) obtained through self-reported measures support its interpretation as a substantive dimension of general order. **Method:** We estimated oblique and orthogonal bifactor exploratory structural equation models of the Big Five. **Results:** The GFP explained considerably less variance than the five group factors, and showed poor model-based reliability. The pattern of GFP loadings were consistent with those of a reverse-keyed wording factor. When related to an external variable (dispositional optimism) the GFP was primarily associated to method variance, and not to the substantive criterion. **Conclusions:** Although there is a certain degree of variance common to most behavioral indicators of personality, its properties are not compatible with an interpretation of the GFP as a reliable and psychometrically meaningful general factor of personality.

Keywords: Five Factor Personality Model, General Factor of Personality, Bifactor, Exploratory Structural Equation Modelling

1. Introduction

The five-factor model (FFM or Big Five) is possibly the dominant conceptualization of personality structure. The FFM assumes that the five basic dimensions of personality are orthogonal (Costa & McCrae, 1992) and thus placed at the highest hierarchical level of personality structure. However, it has been repeatedly shown that the Big Five are not empirically independent; rather, they exhibit correlations of variable but not negligible magnitude. This fact has led the scientific community to hypothesize the existence of non-modeled broader factors as an explanation for these correlations (Digman, 1997), generating a growing interest in the study of potential higher order dimensions of personality.

Since Muecke's (2007) seminal study, research has proliferated regarding theoretical and empirical support for a general factor of personality (GFP; Just, 2011). Substantive interpretations view the GFP as a general dimension representing different adaptation and survival strategies in multiple domains of life, whose positive pole reflects a combination of high levels of stability, extraversion, intellect, agreeableness, and conscientiousness (Rushton, Bons, & Hur, 2008). In the last ten years, a broad field of research has emerged, with the aim of investigating the GFP as a substantive cause of general systematic variance (Rushton & Irwing, 2008), its role in broader nomological networks and as a predictor of relevant outputs (Van der Linden, Nijenhuis, & Bakker, 2010), and its relationship with other constructs such as general intelligence (Dunkel, 2013).

However, the hypothesis of the GFP as a mega-trait at the apex of human personality has not been without criticism (Ferguson, Chamorro-Premuzic, Pickering, & Weiss, 2011). One of the most frequent arguments has been that the low correlations between basic personality factors, as well as the strength and regularity with which the indicators saturate in the GFP are insufficient to postulate the existence of a general factor useful for the assessment of personality beyond the five traditional dimensions. Alternative approaches to studying the

GFP have suggested that the shared variance between indicators belonging to different domains is due to an artifact related to the evaluative valence of items (Bäckström & Björklund, 2016), response trends associated with general self-evaluative traits such as self-esteem (Anusic et al., 2009), or a combination of both (Davies et al., 2015). Moreover, Revelle and Wilt (2013) demonstrated that some of the procedures used in previous studies to estimate the amount of variance explained by the GFP have not been adequate (e.g., interpreting the size of the first eigenvalue in exploratory factor analysis as an indicator of the presence of a general factor). Instead, these authors suggested the use of other indices, such as explained common variance and the coefficient omega hierarchical, as an optimal means of assessing the unidimensionality of the model and accurately quantifying the ratio of reliable variance captured by the general factor. When Revelle and Wilt estimated these indices on eight datasets, they found that the GFP tended to explain little reliable variance and focused its saturations on certain sub-sets of items. However, the number of studies that have used these indexes to assess the psychometric properties of the GFP remains very limited (Davies et al., 2015).

1.1 The present study

In a strict sense, a factor is a mathematical abstraction derived from the empirical covariance between a set of variables, which may (or may not) be interpreted as a common, substantive cause underlying a set of observable behaviors. Interpreting the GFP as a true reflection of individual differences in personality requires the factor to be reliable, large enough to be psychologically and psychometrically meaningful, replicable, and ultimately, useful for personality assessment above and beyond the traditional five factors.

The aim of the present study was to investigate whether the psychometric properties of the GFP and its correlates with external variables support its interpretation as a general entity with causal activity over all personality indicators of a given instrument. Specifically, we

evaluated (a) the degree of unidimensionality present in the FFM model, (b) the accuracy with which a FFM based instrument measures the GFP, and (d) the relation of the GFP with an external variable (dispositional optimism) that is known to be related with the Big Five (Sharpe, Martin, & Roth, 2011). To this end, we conducted a study in two steps. In the first step we compared the fit and internal structure of three models: an oblique first order model, an orthogonal bifactor exploratory structural equation model (ESEM; Asparouhov & Muthen, 2009), and an exploratory factorial model with random intercepts (RI-FA; Maydeu-Olivares & Coffman, 2006). The oblique first order model represents the structure of the Big Five most frequently proposed in the literature (five correlated first order factors). The bifactor model (Reise, 2012) consists of a general factor measured by all the indicators, and j group factors, typically specified according to the previous theory regarding the structure of the construct of interest (the Big Five in the present study). The bifactor model is an alternative specification of the second order model (Reise, 2012). However, contrary to second-order models, the bifactor (a) allows quantifying the direct effect of the general factor on observable variables without the need for such a relationship to be fully mediated by group factors, and (b) facilitates independent evaluation of the merits of general and group factors (e.g., explained variance and model-based reliability). Underlying this model is the hypothesis that there is a general personality factor with causal influence on all items. Finally, the RI-FA model is also composed of five specific factors and a general factor. Here, however, the general factor explicitly reflects systematic variance associated with blind response patterns to item content such as acquiescence. Consequently, the hypothesis underlying the RI-FA model is of a common factor without a substantive relationship with the personality measure.

In the second step, we investigated the correlates of the GFP with regard to an external variable (dispositional optimism). Dispositional optimism can be defined as a generalized tendency to believe that one will generally experience good (or bad, in the case of the

pessimistic pole) outcomes in life (Scheier, Carver, & Bridges, 1994). We believe it is possible to hypothesize a significant and positive relationship between GFP and dispositional optimism. From a substantive point of view, and according to the interpretation proposed by Musek (2007), GFP could be interpreted as a bio-psychological disposition that produces relevant covariations between personality affective bases, thus influencing related domains such as emotionality, self-esteem, motivation, well-being and disposition to optimism/pessimism. On the other hand, the interpretation of GFP as a general feature of human adaptation would support the previous prediction, since dispositional optimism is related to higher coping capacity and less degree of negative affect (Andersson, 1996). From a statistical point of view, previous research suggests that dispositional optimism is consistently related to the five major personality factors: to a greater extent with stability and extraversion, moderately with agreeableness and conscientiousness, and to a lesser extent with intellect (Sharpe, Martin, & Roth, 2011). Given the above, it is expected that if GFP represents substantive variance common to all personality factors, it will capture some of the correlates between personality group factors and dispositional optimism. In contrast, if GFP is representing a non-substantive source of variance, it is not expected to be strongly related to the criterion.

2. Materials and methods

2.1 Participants

The sample consisted of 372 native English speakers of U.S. nationality (age range=18-72, $M=34.2$, $SD=12.7$; 47.7% women) with diverse levels of educational attainment (no formal qualification: 2%; high school: 18.8%; college: 27.7%; undergraduate degree: 37.1%; graduate degree: 8.4%; doctoral degree: 2%). The data were gathered during January 2017 through Prolific Academic, a service supported by Oxford University that specializes in online data gathering using panels of participants defined in advance by the researcher. The

evaluation was completely anonymous, and the participants' consent was obtained to use their responses in research. The raw data used in this study can be downloaded at https://www.dropbox.com/s/5olgwtnr7zf0lwq/raw_data.sav?dl=0.

2.2 Instruments

The Mini-IPIP scale (Donnellan, Oswald, Baird, & Lucas, 2006) is an abbreviated version of the 50-item version of the IPIP Big Five factor markers (Goldberg, 1992), consisting of 20 items, 4 per personality dimension: Extraversion (EX), Agreeableness (AG), Conscientiousness (CO), Neuroticism/Emotional Stability (ES), and Intellect (IN). Each item is answered on a Likert five-point scale according to the degree to which each statement is applicable to the respondent's habitual behavior. As reported in four studies by Donnellan et al., (2006), the average internal consistency indexes (Cronbach's α) of this version are .81 (EX), .73 (AG), .70 (CO), .74 (ES) and .69 (IN). Correlation and fit indices also supported the construct, convergent and discriminant validity according to broader Big Five measures. The reliability of the sub-scales in our data was at acceptable levels (see table 2), with ordinal alpha values between .91 (EX) and .72 (AG).

To assess dispositional optimism in the second step, we used the Life Orientation Test Revised (LOT-R; Scheier, Carves, & Bridges, 1994). The LOT-R consists of six items that measure dispositional optimism (three items reflecting the optimism pole, and three the pessimism pole) plus four filler items. For this study we used the six central items, retaining the same scale of response as in the case of mini-IPIP. Theoretically, the LOT-R represents a one-dimensional construct. However, the presence of a negative wording effect has been observed. This requires the inclusion in the model of a method factor related to wording polarity to achieve an adequate fit (Maydeu-Olivares & Coffman, 2006; Weijters, Baumgartner, & Schillewaert, 2013). To test if this effect appeared in our data, we estimated two initial LOT-R confirmatory models; a one-dimensional model, and a correlated trait-

correlated method minus 1 model (CTCM-1, Eid, 2000), composed of Optimism as a primary factor measured by all the items and an independent residual factor measured by the three inverse items. The one-dimensional model obtained a sub-optimal fit (RMSEA = .119, CFI = .937, TLI = .985), significantly improved in the CTCM-1 model (RMSEA=.058, CFI=.987, TLI=.975). Despite the presence of the wording factor, the primary factor loadings were relatively high (from .68 to .87), with McDonald's omega and ordinal alpha values of .91 and .90, respectively. Consequently, we use the CTCM-1 model of the LOT-R for the rest of the analysis.

2.3 Data analysis

2.3.1 Fitting the models

In the first phase of the analysis, we proceeded to fit exploratory structural equation models (ESEM) for the Mini-IPIP. The ESEM (Asparouhov & Muthen, 2009) is a general technique of factor analysis that allows the estimation of all possible crossloadings in the model. The choice of ESEM instead of the independent cluster model of confirmatory factor analysis (ICM-CFA) was based on the fact that ESEM tends to provide more accurate estimates of loadings and factor correlations, prevents artificial inflation of the general factor loadings, and has been shown to be more effective than the ICM-CFA in the estimation of complex models with interstitial relations between items belonging to different facets/dimensions (Marsh, Morin, Parker, & Kaur, 2014; Morin, Arens, & Marsh, 2016).

Model M1 consisted of five correlated factors (EX, AG, CO, ES, and IN; see Figure 1a). Model M2 consisted of an orthogonal bifactor structure (see 1.1 in introduction and Figure 1b for a conceptual representation) composed of the five personality group factors plus a general factor, common to all items. M2 hypothesizes the presence of a general underlying factor with causal activity over all the behaviors described by the items, which explains the correlations

between factors observed in the oblique model. Finally, Model M3 (Figure 1c) consisted in five ESEM first order factors plus a confirmatory random intercept factor common to all items (RIF). The random intercept factor analysis (RI-IFA; Maydeu-Olivares & Coffman, 2006; Aichholzer, 2014) hypothesizes the existence of a general non-substantive systematic source of variance. Its structure is similar to that of a bifactor model, but in this case the RIF explicitly represents common method variance (e.g., response artifacts such as acquiescence) by imposing an artificial relationship between the items with different wording polarity (Maydeu-Olivares & Coffman, 2006). The RIF is orthogonal to the substantive dimensions, and its loadings are fixed to equality (as a consequence, the RIF occupies a single degree of freedom, corresponding to its variance).

[Please insert Figure 1 here]

Finally, a series of correlations between residuals to be released in all models were established a priori to prevent (a) the estimation of substantive loadings from being biased by the presence of spurious variance due to the semantic similarity of certain pairs of items (Cole, Ciesá, & Steiger, 2007) and (b) such residual systematic variance from being captured by the general factor in the bifactor model. We freed correlations between pairs of items that simultaneously (a) belonged to the same facet, (b) showed high similarity of wording and/or content, and (c) presented extreme modification indices and standardized expected parameter changes in the oblique model. Two pairs met the three conditions (“Have a vivid imagination”/ “Do not have a good imagination” and “I sympathize with others' feelings”/ “I feel others' emotions”).

In all models, target rotation was used, which allows a priori specification of a matrix of primary loadings and crossloadings, enabling the use of ESEM in a confirmatory manner (Asparouhov & Muthén, 2009). Robust maximum likelihood (MLR) was used as estimation algorithm. Goodness of fit was evaluated using the comparative fit index (CFI), the Tucker-

Lewis Index (TLI), the root mean square error of approximation (RMSEA), the Akaike Information Criterion (AIC) and the Bayesian information Criterion (BIC). CFI and TLI values greater than .90 are considered adequate, as are RMSEA values of less than .08 (Hu & Bentler, 1999). Smaller AIC and BIC values are preferred. All analyses were performed using Mplus v. 7.3 (Muthén & Muthén, 1998-2012).

2.3.2 Assessment of the GFP psychometric properties

Fit indices help to decide which model is more plausible, but do not report on the variance explained or on the reliability of the scores derived from each factor, information necessary to decide if a dimension is useful for measuring the hypothesized trait. The psychometric properties of the GFP were evaluated by estimating the explained common variance (ECV; Ten Berge & Socan, 2004), the total variance (ETV) captured by the GFP and by the five group factors, and the coefficient omega hierarchical (ω_h ; Zinbarg, Revelle, Yovel, & Li, 2005). The ECV is the proportion of common variance explained by each of the sources of systematic variability, isolating the effect of the other factors (in ESEM, the effect of crossloadings is also isolated). The ECV of the general factor can be interpreted as an index of one-dimensionality of the model; thus, values greater than .70 suggest that the measure is essentially one-dimensional (Reise, 2012). Coefficient ω_h can be interpreted as the reliable systematic variance in unit-weighted composite raw scores that is attributable to the general factor. Consequently, ω_h is an estimator of the precision with which the scores in the general factor reflect the subject's position in that same latent variable once the effect of the group factors has been partialized (i.e., a low ω_h (<.50) implies that the overall scores on the scale are measuring the general factor quite poorly).

2.3.3 Assessment of GPF external correlates

First, the base model of LOT-R was estimated. Since, as expected, the one-dimensional model did not present a good fit, a new model was estimated where the presence of wording

method variance was considered. We used an ESEM version of the correlated traits-correlated minus one model approach (CTC (M-1), Eid, 2000) similar to that used by Arias & Arias (2017). This model consisted of a substantive factor of Optimism common to all items, and a non-reference factor, orthogonal to the general trait, targeted by the reverse-keyed items, whose function was to capture residual variance related to the wording polarity of the items. Finally, an extended measurement model, composed of the bifactor model of the mini-IPIP (M2) and the LOT-R CTC (M-1) was estimated. All possible correlations among factors were allowed, except for those necessary for the identification of the measurement models.

3. Results

3.1 Fitting the models

The fit indices of the models are shown in Table 1. M1 presented a rather poor fit (RMSEA =.103, CFI =.837; TLI =.690), which was substantially improved by the release of the two correlations between the residuals mentioned above (M2; RMSEA =.056; CFI =.953; TLI =.909). The bifactor model (M3) presented a substantially better fit than that of M2 (RMSEA =.019; CFI =.995; TLI =.989). The RI-FA also presented a substantial improvement with respect to the oblique model, especially considering that there is only one degree of freedom of difference between the two models (RMSEA =.039; CFI =.977; TLI =.956), surpassing the bifactor model for the BIC index.

[Please insert Table 1 here]

The correlations between factors in M1 were generally low (Mean =.14; SD =.09), ranging from .00 (Extroversion-Conscientiousness) to .31 (Agreeableness-Intellect). The correlations between the two pairs of residuals were significant (.48 and .61; $p < .001$). Tables 2 and 3 show the standardized factor loadings of M1 and M2. In M1 a clear structure is observed, with salient primary loadings and small or non-significant cross-loadings. In M2 the pattern of primary loadings of the five specific factors was similar to that found in M1,

although (as expected) the loadings tend to be slightly smaller. The loadings of the general factor were in a range between $-.10$ and $.54$ ($|\text{Mean}| = .26$; $SD = .19$). Considering the pattern of salient loadings, it was observed that 71% of the variance captured by the GFP was concentrated in the negative-keyed items.

[Please insert Table 2 here]

[Please insert Table 3 here]

3.2 Assessment of the GFP psychometric properties

Table 3 shows the ECV, hierarchical and sub-scale omega, and the reliable variance ratio obtained from the parameters of the bifactor model. For ease of interpretation, Figure 2 represents the distribution of ECV and ETV. The ECV captured by the GFP was $.17$. Specific factors as a whole accounted for $.77$ of the common variance. These results imply that most of the common variance was attributable to group factors and that the measure had a very low level of unidimensionality. The distribution of total variance of GFP ($ETV = .11$) confirmed the findings above, as the general factor had very little explanatory power on the total variability observed in the data once the effect of the group factors, the crossloadings, and the residual variance were partialized. The ω and ω_h values of the GFP were $.77$ and $.37$, respectively. As a consequence, the general factor captured little reliable variance in unit-weighted composite raw scores, given that 48% of the reliable variance in composite scores can be attributed to the GFP ($\omega/\omega_h = .48$).

[Please insert Figure 2 here]

3.3 Correlates of GFP with external variables

The one-dimensional model of LOT-R showed an unacceptable fit ($RMSEA = .101$; $CFI = .879$; $TLI = .889$). By introducing the wording factor, the fit was significantly improved ($RMSEA = .045$; $CFI = .965$; $TLI = .945$). The extended measurement model showed adequate fit (M7, Table 1). Correlations between personality factors, optimism and the wording factor

are shown in Table 4. According to expectations (Sharpe, Martin, & Roth, 2011), emotional stability and extraversion showed the highest correlations with optimism (.66 and .43, respectively), followed by low correlations with agreeableness (.18), conscientiousness (.21) and no significant correlation with intellect (.11). The GFP did not correlate significantly with optimism (.03, ns). The wording factor did not show a significant relationship with personality factors, except for extraversion (.21, $p < .05$). The GFP showed high correlation with the LOT-R wording factor (.66, $p < .01$).

[Please insert Table 4 here]

4. Discussion

The present study aimed to evaluate psychometric properties relevant to the interpretation of the general factor of personality. To this end, we estimated ESEM bifactor models on a scale based on the big five model. According to our results: (a) the GFP explained substantially less common and total variance than the group factors, (b) once the effect of the group factors was partialized, the GFP did not reach sufficient reliability to guarantee its meaningful psychometric interpretation (at least as a general order factor), and (c) all items were far better indicators of the five personality domains than of the general dimension.

These results suggest that: (a) there is no (at least in our data) empirical support for reifying the GFP as a cause common to all personality observable behaviors, and (b) the utility of the GFP as a predictor, at least in the context of factorial analysis, is questionable due to its low reliability. Furthermore, these results are highly consistent with those of studies that have estimated hierarchical omega by confirmatory factor analysis (Davies et al., 2015; Revelle & Wilt, 2013). On the other hand, the factor loadings pattern of GFP was compatible with its interpretation as a wording factor, given that the majority of the variance captured by the GFP was concentrated in the negatively-keyed items. The above was compatible with the fact that the bifactor model acquired a fit similar to those of the random intercept model,

where the general factor explicitly represents common method variance. Furthermore, the GFP showed no significant relation to an external criterion (dispositional optimism), but rather with a wording factor whose function was to model systematic variance, presumably associated with incoherent response patterns. This is a first evidence that GFP may be in part capturing method variance, and therefore be closer to a common method factor than to a general personality dimension. However, it is necessary to interpret these correlations with caution, given the possibility that negative wording factors are in part capturing substantive variance (Arias & Arias, 2017).

Our results are not compatible with an interpretation of the GFP as a dimension hierarchically superior to the five basic factors of personality. However, the inclusion of a general factor substantially improved the fit with respect to the five correlated factors models. Consequently, there is a certain amount of general systematic variance that, although unstable in size and definition, emerges in various samples and instruments. However, the variability in the type of items that load most in the GFP supports the hypothesis that the GFP is essentially systematic variance associated with specific sets of indicators, to a greater extent than a general tendency of self-evaluation or a broader substantive trait. This is compatible with the hypothesis that the GFP is dependent on the evaluative valence of the items (Bäckström & Björklund, 2016), so that in sets of indicators with neutral valence, the GFP would tend to weaken.

Finally, it is necessary to take into account the limitations of this study, such as the use of a non-probabilistic sample, and especially that we relied on a single tool based on self-reported data. It would therefore be necessary to replicate the exposed results in broader samples and with diverse response formats (e.g., hetero-informed measures). Furthermore, although the empirical GFP appears not to behave as a truly "general" personality factor in this study, it is possible that specifying a general dimension in a factorial model is not the

only viable way to investigate the origin of positive manifold observed between indicators of theoretically orthogonal traits. Alternative analysis techniques, such as the integration of networks into latent variable models (Epskamp, Rhemtulla, & Borsboom, 2017), may provide useful information for research on the nature of the GFP in the future.

References

- Aichholzer, J. (2014). Random intercept EFA of personality scales. *Journal of Research in Personality, 53*, 1-4. doi:10.1016/j.jrp.2014.07.001
- Andersson, G. (1996). The benefits of optimism: A meta-analytic review of the Life Orientation Test. *Personality and Individual Differences, 21*(5), 719-725. doi:10.1016/0191-8869(96)00118-3
- Anusic, I., Schimmack, U., Pinkus, R. T., & Lockwood, P. (2009). The nature and structure of correlations among Big Five ratings: The halo-alpha-beta model. *Journal of Personality and Social Psychology, 97*, 1142-1156. doi:10.1037/a0017159
- Arias, V. B., & Arias, B. (2017). The negative wording factor of Core Self-Evaluations Scale (CSES): Methodological artifact, or substantive specific variance? *Personality and Individual Differences, 109*, 28-34. doi:10.1016/j.paid.2016.12.038
- Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 16*(3), 397-438. doi:10.1080/10705510903008204
- Bäckström, M., & Björklund, F. (2016). Is the general factor of personality based on evaluative responding? Experimental manipulation of item-popularity in personality inventories. *Personality and Individual Differences, 96*, 31-35. doi:10.1016/j.paid.2016.02.058

- Cole, D. A., Ciesla, J. A., & Steiger, J. H. (2007). The insidious effects of failing to include design-driven correlated residuals in latent-variable covariance structure analysis. *Psychological Methods, 12*(4), 381. doi:10.1037/1082-989X.12.4.381.
- Costa, P. T., & McCrae, R. R. (1992). 4 ways 5 factors are basic. *Personality and Individual Differences, 13*, 653-665. doi:10.1016/0191-8869(92)90236-I
- Davies, S. E., Connelly, B. S., Ones, D. S., & Birkland, A. S. (2015). The General Factor of Personality: The "Big One," a self-evaluative trait, or a methodological gnat that won't go away? *Personality and Individual Differences, 81*, 13-22.
doi:10.1016/j.paid.2015.01.006
- Digman, J. M. (1997). Higher-order factors of the Big Five. *Journal of Personality and Social Psychology, 73*(6), 1246-1256. doi:10.1037/0022-3514.73.6.1246
- Donnellan, M. B., Oswald, F. L., Baird, B. M., & Lucas, R. E. (2006). The mini-IPIP scales: tiny-yet-effective measures of the Big Five factors of personality. *Psychological Assessment, 18*(2), 192-203. doi:10.1037/1040-3590.18.2.192
- Dunkel, C. S. (2013). The general factor of personality and general intelligence: Evidence for substantial association. *Intelligence, 41*(5), 423-427. doi:10.1016/j.intell.2013.06.010
- Eid, M. (2000). A multitrait-multimethod model with minimal assumptions. *Psychometrika, 65*(2), 241-261. doi:10.1007/BF02294377
- Epskamp, S., Rhemtulla, M., & Borsboom, D. (2017). Generalized network psychometrics: Combining network and latent variable models. *Psychometrika, 82*(4), 904-927.
doi:10.1007/s11336-017-9557-x
- Ferguson, E., Chamorro-Premuzic, T., Pickering, A., & Weiss, A. (2011). Five into one doesn't go: Critique of the general factor of personality. In T. Chamorro-Premuzic, S. von Stumm, & A. Furnham (Eds.), *The Wiley-Blackwell handbook of individual differences*. London: Wiley-Blackwell.

- Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment, 4*(1), 26-42. doi:10.1037/1040-3590.4.1.26
- Just, C. (2011). A review of literature on the general factor of personality. *Personality and Individual Differences, 50*(6), 765-771. doi:10.1016/j.paid.2011.01.008
- Marsh, H. W., Morin, A. J., Parker, P. D., & Kaur, G. (2014). Exploratory structural equation modeling: An integration of the best features of exploratory and confirmatory factor analysis. *Annual Review of Clinical Psychology, 10*, 85-110. doi:10.1146/annurev-clinpsy-032813-153700
- Maydeu-Olivares, A., & Coffman, D. L. (2006). Random intercept item factor analysis. *Psychological Methods, 11*(4), 344-362. doi:10.1037/1082-989X.11.4.344
- Morin, A. J., Arens, A. K., & Marsh, H. W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling: A Multidisciplinary Journal, 23*(1), 116-139. doi:10.1080/10705511.2014.961800
- Musek, J. (2007). A general factor of personality: Evidence for the Big One in the Five-Factor. *Journal of Research in Personality, 41*(6), 1213-1233. doi:10.1016/j.jrp.2007.02.003
- Muthén B. O., & Muthén L. K. (1998-2012). Mplus User's Guide (6th Ed.). Los Angeles, CA: Muthén & Muthén.
- Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research, 47*(5), 667-696. doi:10.1080/00273171.2012.715555
- Revelle, W., & Wilt, J. (2013). The general factor of personality: A general critique. *Journal of Research in Personality, 47*(5), 493-504. doi:10.1016/j.jrp.2013.04.012
- Rushton, J. P., & Irwing, P. (2008). A general factor of personality (GFP) from two meta-analyses of the Big Five: Digman (1997) and Mount, Barrick, Scullen, and Rounds

- (2005). *Personality and Individual Differences*, 45, 679-683.
doi:10.1016/j.paid.2008.07.015
- Rushton, J. P., Bons, T. A., & Hur, Y. M. (2008). The genetics and evolution of a general factor of personality. *Journal of Research in Personality*, 42, 1173-1185.
doi:10.1016/j.jrp.2008.03.002
- Scheier, M. F., Carver, C. S., & Bridges, M. W. (1994). Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): A re-evaluation of the Life Orientation Test. *Journal of Personality and Social Psychology*, 67, 1063-1078.
doi:10.1037/0022-3514.67.6.1063
- Sharpe, J. P., Martin, N. R., & Roth, K. A. (2011). Optimism and the Big Five factors of personality: Beyond neuroticism and extraversion. *Personality and Individual Differences*, 51(8), 946-951. doi:10.1016/j.paid.2011.07.033
- Ten Berge, J. M. F., & Socan, G. (2004). The greatest lower bound to the reliability of a test and the hypothesis of unidimensionality. *Psychometrika*, 69(4), 613-625.
doi:10.1007/BF02289858
- Van der Linden, D., Nijenhuis, J., & Bakker, A. B. (2010). The general factor of personality: A meta-analysis of Big Five intercorrelations and a criterion-related validity study. *Journal of Research in Personality*, 44, 315-327. doi:10.1016/j.jrp.2010.03.003
- Weijters, B., Baumgartner, H., & Schillewaert, N. (2013). Reversed item bias: An integrative model. *Psychological Methods*, 18(3), 320-334. doi:10.1037/a0032121
- Zinbarg, R. E., Revelle, W., Yovel, I., & Li, W. (2005). Cronbach's alpha, Revelle's beta, and McDonald's omegah: Their relations with each other and two alternative conceptualizations of reliability. *Psychometrika*, 70, 123-133.
doi:10.1007/s11336-003-0974-7