Diamantopoulos, A., Riefler, P., & Roth, K. P. (2008). Advancing formative measurement models. *Journal of Business Research*, *61*, 1203–1218. http://doi.org/10.1016/j.jbusres.2008.01.009

Edwards, J. R. (2001). Multidimensional constructs in organizational behavior research: An integrative analytical framework. *Organizational Research Methods*, *4*, 144–192. http://doi.org/10.1177/109442810142004

Fleishman, E. A., Quaintance, M. K., & Broedling, L. A. (1994). *Taxonomies of human performance: The description of human tasks*. Orlando, FL: Academic Press.

Gottfredson, L. S. (1997). Mainstream science on intelligence: An editorial with 52 signatories, history, and bibliography. *Intelligence*, *24*, 13–23. http://doi.org/10.1016/S0160-2896(97)90011-8

Haertel, E. H. (2013). *Reliability and validity of inferences about teachers based on student test scores*. Princeton, NJ: Educational Testing Service. Retrieved from https://www.ets.org/Media/Research/pdf/PICANG14.pdf

Johnson, W., Nijenhuis, J., & Bouchard, T. J., Jr. (2008). Still just 1 *g*: Consistent results from five test batteries. *Intelligence*, *36*, 81–95. http://doi.org/10.1016/j.intell.2007.06.001

Judge, T. A., Hulin, C. L., & Dalal, R. S. (2012). Job satisfaction and job affect. In S. W. J. Kozlowski (Ed.), *The Oxford handbook of organizational psychology* (Vol. 1, pp. 496–525). New York, NY: Oxford University Press. http://doi.org/10.1093/oxfordhb/9780199928309.013.0015

Ree, M. J., Carretta, T. R., & Teachout, M. S. (2015). Pervasiveness of dominant general factors in organizational measurement. *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *8*(3), 409–427.

Reeve, C. L., Scherbaum, C., & Goldstein, H. (2015). Manifestations of intelligence: Expanding the measurement space to reconsider specific cognitive abilities. *Human Resource Management Review*, *25*, 28–37.

Schmidt, F. L., & Kaplan, L. B. (1971). Composite vs. multiple criteria: A review and resolution of the controversy. *Personnel Psychology*, *24*, 419–434. http://doi.org/10.1111/j.1744-6570.1971.tb00365.x

Wiernik, B. M., Wilmot, M. P., & Kostal, J. W. (2015). How data analysis can dominate interpretations of dominant general factors. *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *8*(3).

Estimating the Strength of a General Factor: Coefficient Omega Hierarchical

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Relying on work described by Jackson (2003), Ree, Carretta, and Teachout (2015) recommended researchers use the first unrotated principal

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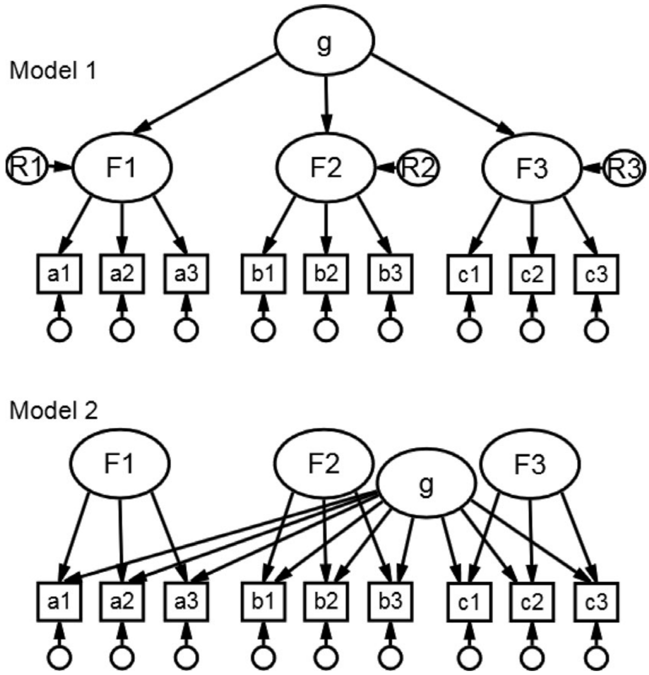

Figure 1. The two most common models used to estimate general factor variance in structural equation modeling (Model 1 = higher order model; Model 2 = bifactor model). F = factor; R = residual; g = general factor; a, b, and c = observed indicators.

component associated with a principal components analysis (PCA) to estimate the strength of a general factor. Arguably, such a recommendation is based on rather old work. Furthermore, it is not a method that can be relied on to yield an accurate solution. For example, it is well known that the first component extracted from a correlation matrix of the Wechsler intelligence subtests is biased toward the verbal comprehension subtests (Ashton, Lee, & Vernon, 2001).

In contrast to the first unrotated principal component, it is arguably important for industrial–organizational researchers to be aware of the options of estimating the strength of a general factor via structural equation modeling (SEM). Within the context of multidimensional models, a general factor can be specified within a higher order model (see Model 1, Figure 1) or as a first-order breadth factor represented within a bifactor model (see Model 2, Figure 1). Based on either a higher order model or a bifactor model solution, the strength of a general factor can be estimated via an attractive coefficient known as omega hierarchical (ω_h; Zinbarg, Revelle, Yovel, & Li, 2005). Coefficient ω_h represents the strength of a general factor on a standardized metric and ranges from .00 to 1.0. It is essentially the ratio of common variance to total variance and can be estimated relatively easily in most SEM programs (see Gignac, 2014b, for step-by-step instructions). A coefficient ω_h of .80, for example, would imply that the general factor accounts for 80% of the total variance in the data. Gignac and Watkins (2013) found that the general factor associated with the Wechsler Adult Intelligence Scale–IV (Wechsler, 2008) was associated with a very large ω_h of .86. Thus, Ree et al. are correct to contend that there are some very large general factors that can be found in the literature. I suspect the general factor of personality discussed by Ree et al. would be very weak by comparison, however, when modeled and estimated appropriately via ω_h (see Revelle & Wilt, 2013, for example).

What makes a model-based coefficient such as ω_h particularly attractive is that it is derived from either a higher order model or a bifactor model, both of which partition the various sources of common variance into separate terms. For example, in the context of the Wechsler scales, the substantial common variance associated with verbal subtests can be "controlled" through the specification of a nested factor in a bifactor model (say, the "F1" term in Model 2). Alternatively, a higher order model would specify the unique common variance associated with the verbal subtests as a first-order factor residual (say, the "R1" term in Model 1).[1] As the verbal common variance is associated with its own term, it does not contaminate the general factor. Consequently, the strength of the general factor can be estimated accurately via ω_h.

Although the higher order model and the bifactor model have some similarities, there are at least two key differences. First, the higher order model imposes a proportionality constraint on the association between the observed variables and the latent variables[2] (Schmiedek & Li, 2004). For this reason, the bifactor model tends to fit better than does the competing higher order model (Gignac, 2008; Reise, 2012). Second, because of issues relevant to identification, only the bifactor allows for the simultaneous estimation of effects associated with all of the latent variables (general factor and nested factors) and a dependent variable of interest (Schmiedek & Li, 2004). Across a number of considerations, the bifactor model may be considered preferable in the context of estimating the effects of a general factor and competing specific factors on a dependent variable (Brunner, 2008). Whether one prefers a higher order or a breadth conceptualization of a general factor is irrelevant, as omega hierarchical can be applied to both. A similar coefficient, omega specific (ω_s; Reise, 2012), can also be used to estimate the strength of

1 The addition of correlated uniqueness between common subtest residuals is another model from which coefficient ω_h could be estimated (i.e., the single-trait correlated uniqueness model; Gignac, 2006).

2 I use the term "latent variables" in this context to refer to both the higher order factors and the residuals associated with the lower order factors.

secondary factors independently of the effects of the general factor (see Gignac, 2014b, for an accessible demonstration).

The estimation of the strength of a general factor is not a purely statistical or psychometric consideration, as interesting theories can be tested with such information. For example, Gignac (2014a) tested the dynamic mutualism theory of general intelligence by plotting the strength of the general factor (ω_h) across the ages of 2.5 to 90 years. The results suggested that the strength of the general factor (*g*) is largely constant across age, which was considered a failure to support the dynamic mutualism theory of *g* (van der Maas et al., 2006). Almost undoubtedly, many more useful hypotheses could be tested with ω_h across many disciplines in psychology. Thus, in line with Ree et al., researchers are encouraged to consider the strength of a general factor in their data. However, I would urge all researchers to decline the option of the first component derived from a PCA, in favor of a sophisticated method such as ω_h.

References

Ashton, M. C., Lee, K., & Vernon, P. A. (2001). Which is the real intelligence? A reply to Robinson (1999). *Personality and Individual Differences*, *30*, 1353–1359.

Brunner, M. (2008). No *g* in education? *Learning and Individual Differences*, *18*(2), 152–165.

Gignac, G. E. (2006). Evaluating subtest "*g*" saturation levels via the single trait-correlated uniqueness (STCU) SEM approach: Evidence in favor of crystallized subtests as the best indicators of "g." *Intelligence*, *34*, 29–46.

Gignac, G. E. (2008). Higher-order models versus bifactor modes: *g* as superordinate or breadth factor? *Psychology Science*, *50*(1), 21–43.

Gignac, G. E. (2014a). Dynamic mutualism versus *g* factor theory: An empirical test. *Intelligence*, *42*, 89–97.

Gignac, G. E. (2014b). On the inappropriateness of using items to calculate total scale score reliability via coefficient alpha for multidimensional scales. *European Journal of Psychological Assessment*, *30*, 130–139.

Gignac, G. E., & Watkins, M. W. (2013). Bifactor modeling and the estimation of model-based reliability in the WAIS-IV. *Multivariate Behavioral Research*, *48*, 639–662.

Jackson, J. E. (2003). *A user's guide to principal components*. Hoboken, NJ: Wiley.

Ree, M. J., Carretta, T. R., & Teachout, M. S. (2015). Pervasiveness of dominant general factors in organizational measurement. *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *8*(3), 409–427.

Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research*, *47*, 667–696.

Revelle, W., & Wilt, J. (2013). The general factor of personality: A general critique. *Journal of Research in Personality*, *47*(5), 493–504.

Schmiedek, F., & Li, S. C. (2004). Toward an alternative representation for disentangling age-associated differences in general and specific cognitive abilities. *Psychology and Aging*, *19*(1), 40–56.

van der Maas, H. L., Dolan, C. V., Grasman, R. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, *113*(4), 842.

Wechsler, D. (2008). *Wechsler Adult Intelligence Scale—Fourth Edition*. San Antonio, TX: Pearson Assessment.

Zinbarg, R. E., Revelle, W., Yovel, I., & Li, W. (2005). Cronbach's α, Revelle's β, and McDonald's ω H: Their relations with each other and two alternative conceptualizations of reliability. *Psychometrika*, *70*(1), 123–133.

How Data Analysis Can Dominate Interpretations of Dominant General Factors

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A dominant general factor (DGF) is present when a single factor accounts for the majority of reliable variance across a set of measures (Ree, Carretta, & Teachout, 2015). In the presence of a DGF, dimension scores necessarily reflect a blend of both general and specific factors. For some constructs, specific factors contain little unique reliable variance after controlling for the general factor (Reise, 2012), whereas for others, specific factors contribute a more substantial proportion of variance (e.g., Kinicki, McKee-Ryan, Schriesheim, & Carson, 2002). We agree with Ree et al. that the presence of a DGF has implications for interpreting scores. However, we argue that the conflation of general and specific factor variances has the strongest implications for understanding how constructs relate to external variables. When dimension scales contain substantial general and specific factor variance, traditional methods of data analysis will produce ambiguous or even misleading results. In this commentary, we show how several common data analytic methods, when used with data sets containing a DGF, will substantively alter conclusions.

Job satisfaction is a quintessential multidimensional construct with a DGF. It comprises several dimensions, each of which reflects attitudes toward different components of the job and all of which are simultaneously

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