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Seek and Ye Shall Find

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Being familiar with their earlier work investigating the factor structures of the Armed Services Vocational Aptitude Battery and the Air Force Officer Qualifying Test, we read with interest Ree, Carretta, and Teachout's (2015) proposal to extend the idea of a dominant general factor (DGF) beyond the realm of cognitive abilities to other areas of research and practice in industrial–organizational (I-O) psychology. We found their ideas intriguing

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and their arguments compelling, but we stumbled on a reference to an article of one of the present authors (Lance, Teachout, & Donnelly, 1992) and Ree et al.'s claim that Lance et al. (1992) had found a DGF that accounted for 59% of the variance in job performance ratings in a military job. They did not. Rather, Lance et al. reported a hierarchical confirmatory factor analysis (CFA) model that explained parsimoniously the correlations among 15 job performance first-order factors in terms of four Job Proficiency and four other Measurement Source second-order factors. We reasoned that Ree et al. must have conducted some secondary analysis on the results presented by Lance et al., and indeed we replicated their claim by finding that the first unrotated principal component accounted for 59% of the variance in correlations among the four Proficiency second-order factors reported in Lance et al.'s Table 6.

Skeptics that we are, we sought to determine whether the other studies cited in Ree et al.'s Table 1 to support their claim of ubiquitous DGF effects had been reported as original findings or, rather, as in the case of the Lance et al. study, whether secondary analyses were undertaken to develop the authors' case for DGFs. We were able to obtain original copies of 20 of the 37 studies cited by Ree et al. The remainder consisted of unpublished data sets, unpublished theses and dissertations, proprietary publications, book chapters, military technical reports, or documents otherwise unavailable to us. We will discuss our insights from our review of these studies, but first we consider Ree et al.'s criteria for a DGF.

Criteria for a DGF

Ree et al.'s first criterion for a DGF is that it "must come from the largest source of reliable variance" (p. xx): That is, if it accounts for "a plurality of the variance, it satisfies the first criterion to be considered dominant." Ree et al. recommend the use of principal components analysis (PCA), which "posits no model but is an orthogonal decomposition that will reproduce the correlation/covariance matrix perfectly." The first, unrotated principal component is to be regarded as the DGF. As is well known, the first principal component extracted from a square symmetric matrix will *always* represent the maximum variance explained relative to that explained by orthogonal components extracted subsequently (Harris, 1985), by design, except for zero or identity matrices (or, e.g., $c*\mathbf{I}$ where c is a constant). That's the way PCA works. By this definition, a DGF is guaranteed to emerge from an orthogonal PCA decomposition of *any* correlation matrix, and so, in this sense, this criterion is tautologous.

The second criterion for a DGF is that "every variable measuring the construct must be influenced by the DGF" (Ree et al., p. xx); "if the common factor . . . influenced all of the variables, then it satisfies the second criterion

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to be considered general" (p. xx).[1] By definition, each of *m* variables *will* load on each of the *m* principal components extracted from a positive definite *m* × *m* correlation matrix because PCA is an unrestricted multivariate technique (vs., e.g., CFA, which permits restrictions on model parameter estimates). What we assume Ree et al. meant was that all variables should have *nontrivial* loadings on a DGF. But what is "nontrivial?" One widely cited cutoff for a nontrivial factor loading is |.4| (Ford, MacCallum, & Tait, 1986). Field, Miles, and Field (2012) generally concur but recommend that "if you think that a loading of .4 will be interesting, you should use a lower cutoff (say, .3), because you don't want to miss a loading of .39" (p. 788). But Stevens (2002) suggests that what is considered to be a nontrivial factor loading should vary with sample size from |.70| for $N = 50$ to |.162| for $N = 1{,}000$. Clearly, judging what is a "nontrivial" factor loading is a subjective enterprise.

Does the Finding of a DGF Necessarily Mean That a General Factor Dominates the Data?

No. As Ree et al. note, PCA "posits no model" (p. xx). Could some (other) theoretically motivated model serve just as well, or perhaps even better, to explain the data? Of course (Vandenberg & Grelle, 2009). To illustrate this point we return to the Lance et al. (1992) study. We conducted a PCA on the matrix of correlations among 15 multitrait, multisource performance first-order factors presented in their appendix. The first principal component explained 42% of the variance and component loadings that ranged between .48 and .76, suggesting, according to Ree et al.'s criteria, the presence of a DGF. In fact, Lance et al. also tested for a general factor using hierarchical CFA. They found that the standardized second-order factor loadings ranged between .23 and .98, and all were greater than three times their standard errors, also suggesting a DGF. However, fit for this model was quite poor by conventional standards, $\chi^2(1814, N = 261) = 3{,}709.96$, $p < .001$; standardized root-mean-squared residual (SRMSR) = .107, Tucker-Lewis Index (TLI) = .821, relative normed fit index (RNI) = .700. In contrast, a theoretically based model that contained latent Proficiency and Measurement Source second-order factors provided a much better fit to the data, $\chi^2(1787, N = 261) = 2{,}851.72$, $p < .001$; SRMSR = .067, TLI = .898, RNI = .981. The moral is that although an alleged DGF may be derived from (nearly any) data, it is not a *unique* explanation, and (perhaps many) other theoretically motivated models may provide a (perhaps much) more complete explanation of the data. That is, armed with relevant theory, one will often achieve a more complete and meaningful explanation of the data at hand.

[1] Ree et al. seem to disregard important mathematical distinctions here between the common factor model and the principal component model, perhaps because they allow that either can be used to estimate DGFs.

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Table 1. Summaries of Studies in Which a DGF Was Reported in Original Findings

Study	Construct and % DGF variance reported by Ree et al.	How % DGF variance was calculated in original study	Second criterion for DGF satisfied?	Comments
Carretta et al. (1996)	Pilot situational awareness—92%	Unrotated first PC of 31 peer and supervisor ratings	Indeterminate—results not reported	
Carretta & Ree (1996)	AFQT—41%	CFA with *g* common factor	Yes	G constrained orthogonal to 5 S_i factors in CFA
Carretta & Ree (1997)	Psychomotor tests—39%	CFA with *g* common factor—31%	No. 19/37 loadings on *g* factor < |.20|	G constrained orthogonal to 11 S_i factors in CFA
Musek (2007)	Big 5—50%, 40%, & 45%	PCA of Big 5 scale scores	Yes, generally	Component loading for Openness = .23 in Sample 2
Viswesvaran et al. (2005)	Job performance—60%	CFA of peer & supervisor ratings	Indeterminate—results not reported	6 different estimates of DGF in Table 11 from 56%–99%

Note. DGF = dominant general factor; PC = principal component; AFQT = Air Force Officer Qualifying Test; CFA = confirmatory factor analysis; PCA = principal components analysis.

Our Review of Studies Cited by Ree et al.

Studies in Which Percentage of Variance Accounted for by a DGF Was Reported in Original Findings

Our summary of these studies, of which there were only five, is shown in Table 1. Three of these are from the original body of literature that emanated from the United States Air Force research that concluded there was "not much more than *g*" (e.g., Ree & Earles, 1991) in some of the Air Force's operational measures. We assumed that these studies analyzed and reported their data correctly, and so we did not attempt replication.

Two of the studies in Table 1 used PCA, three used CFA to model the DGF, and all five studies' results met the first criterion for demonstrating a DGF (however, see above). Two of the five studies also met the second DGF criterion of all variables having nontrivial loadings on the DGF; one

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very much did not (Carretta & Ree, 1997), and it could not be ascertained from the remaining two studies whether the second DGF criterion was met. As such, we do not see that either the identity or the ubiquity of DGFs was established by these five studies.

Studies in Which Percentage of Variance Accounted for by a DGF Was Not Reported in Original Findings

Our summary of these studies is shown in Table 2. In none of these studies was an estimate of variance accounted for by a DGF reported originally, so we attempted to replicate Ree et al.'s estimates of the percentage of variance accounted for by a DGF using data presented in the original article that we best guessed were the data that Ree et al. must have also reanalyzed. The presumed sources of these data are listed in the third column of Table 2. Our first finding was that we substantially replicated their results. In several cases, however (Barbuto & Wheeler, 2006; Castro, Scandura, & Williams, 2004; Chan & Drasgow, 2001; Fiori & Antonakis, 2011; Liden & Maslyn, 1998; Rahim & Magner, 1995; Rushton & Irwing, 2008), multiple candidate correlation matrices were reported in the original studies, whereas Ree et al. reported only one DGF variance-accounted-for estimate. Interestingly, in every case but one, Ree et al. chose to report the largest of the available estimates (for the Liden & Maslyn study, Ree et al. reported 61%, whereas PCA indicated 64% variance accounted for in the other correlation matrix reported in the same Table 3).

Second, we noted that data were reported at various levels of analysis in these studies, including correlations among item parcels (Fiori & Antonakis, 2011), subscale scores (e.g., Ahmetoglu, Leutner, & Chamorro-Premuzic, 2011; Barbuto & Wheeler, 2006; Chan & Drasgow, 2001), total scale/test scores (e.g., Judge, Van Vianen, & De Pater, 2004; Rushton & Irwing, 2008), experimental task scores (Ackerman & Cianciolo, 2000), first-order factors (Castro et al., 2004; Parker, Keefer, & Wood, 2011; Rahim & Magner, 1995), and second-order factors (e.g., Lance et al., 1992). Of course there is nothing in Ree et al.'s criteria that precludes the discovery of DGFs at various levels of analysis, but this finding leads us to question whether, for example, a DGF derived from correlations among item parcels (Fiori & Antonakis, 2011) affords the same interpretation as a job performance third-order factor, because factors that are deeper in nomological networks are ordinarily attributed much broader explanatory power (Cronbach & Meehl, 1955).

Third, we noted that most of the correlation matrices that Ree et al. apparently reanalyzed were rather small. Figure 1 shows a frequency plot of matrix sizes with the Stauffer, Ree, and Carretta (1996) outlier (25 tests) removed. The median number of elements analyzed was four. The chances of satisfying both of Ree et al.'s DGF criteria are increased by conducting PCA on correlations among a small number of at least moderately correlated

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Table 2. Attempted Replications of Results From Studies That Did Not Originally Report DGF Findings

Study	Construct	Attempted replication	Comments
Ackerman & Cianciolo (2000)	Psychomotor ability	PCA of correlations (corrs) among 7 experimental tasks reported in Table 7	Abilities treated separately in regression analyses
Ahmetoglu et al. (2011)	Entrepreneurship (ENT)	PCA of 4 subscale score corrs in Table 1	Subscale scores treated as MIs of ENT in an LV model
Barbuto & Wheeler (2006)	Servant leadership	PCA of 5 subscale scores for self and other ratings in Tables 3 & 4	CFA of 23 items supported an oblique 5-factor structure
Castro et al. (2004)	Mentoring	PCA of FOF corrs for 3 samples in Tables 4 & 7	CFA of 15 & 9 item scales supported an oblique 3-factor structure
Chan & Drasgow (2001)	Motivation to lead (MTL)	PCA of corrs among MTL subscales for 3 samples in Table 4	Treated 3 MTL facets separately in path model
Edwards et al. (2008)	Job satisfaction	PCA of JDI composites in Table 1	Treated JDI facets separately as predictors of performance
Fiori & Antonakis (2011)	Emotional IQ (EI)	PCA of 2 different subscale set corrs in Table 1	Treated EI facets separately as criteria
Judge et al. (2004)	Core self-evaluations (CSEs)	PCA of corrs for 4 CSEs in Table 1	Meta-analytic (MA) corrs corrected for attenuation
Krause et al. (2006)	Assessment centers	PCA of dimension corrs in Table 3	Treated dimension scores separately as predictors of performance
Lance et al. (1992)	Military job performance	PCA of SOF corrs in Table 6	HCFA supported 4 proficiency and 4 other measurement source SOFs
Liden & Maslyn (1998)	Leader–member exchange (LMX)	PCA of 4 LMX subscales for 4 samples in Tables 3 & 5	CFA of 11 item scale supported an oblique 4-factor structure
Parker et al. (2011)	Emotional IQ	PCA of FOF corrs in Table 2	CFA supported 4 FOFs plus *g* SOF

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Table 2. (Continued)

Study	Construct	Attempted replication	Comments
Rahim & Magner (1995)	Organizational conflict	PCA of FOF corrs for 3 different test forms in Table 4	CFA of 10 subscales supported an oblique 5-factor structure
Rushton & Irwing (2008)	Big 5 personality	PCA of Big 5 scale scores for 2 MAs in Tables 2 & 3	MA corrs corrected for attenuation
Stauffer et al. (1996)	Cognitive components	PCA of 25 measures in Table 2	HCFA supported a DGF as a SOF

Note. DGF = dominant general factor; PCA = principal components analysis; CFA = confirmatory factor analysis; MIs = manifest indicators; LV = latent variable; SOF = second-order factor; HCFA = hierarchical CFA; FOF = first-order factor; JDI = Job Descriptive Index.

Table 3. DGFs Derived From Random Data

Study	% VAR	PC loadings	Study	% VAR	PC loadings
Study 1	38%	.825	Study 2	31%	.740
		.656			.466
		− .305			.592
		.550			.356
Study 3	32%	− .597	Study 4	34%	.544
		.307			.674
		.407			.100
		.805			.779

Note. DGFs = dominant general factors; VAR = variance; PC = principal component.

variables; larger numbers of variables increase the likelihood of a multidimensional solution (Mardia, Kent, & Bibby, 1979) and failure of Ree et al.'s second DGF criterion. Also, with a small number of moderately correlated variables, a DGF is virtually guaranteed to emerge regardless of whether it is meaningful theoretically. For example, we conducted a PCA on the correlations among the four Measurement Source second-order factors reported in Lance et al.'s (1992) Table 6 and, not surprisingly, a DGF emerged, accounting for 42% of the variance and principal component loadings ranging between .48 and .76. Correlations among these second-order factors are sensical and are easily interpretable as indicating degree of intersource agreement, but how is a third-order DGF to be interpreted in this case?

We present evidence of DGFs for four other data sets in Table 3. In each case the first principal component explains a plurality of the variance and, with the exception of one loading in Study 4, all principal component

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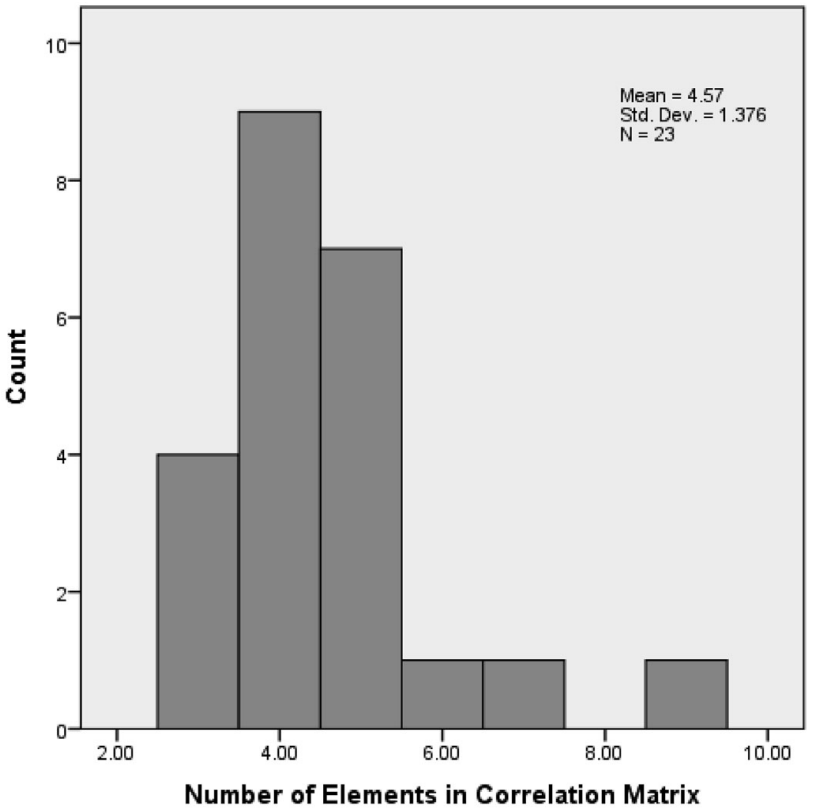


Figure 1. Number of elements in correlation matrices analyzed in our replication of Ree et al.'s findings.

loadings meet conventional (if slightly liberal) criteria for nontrivial principal component loadings (see above). However, the data are entirely random; results in Table 3 are from a PCA of 50 observations each[2] on four independent (i.e., uncorrelated), normally distributed random variables.[3] Thus, even when a correlational structure arises entirely from sampling error, PCA still does its job of extracting the maximum variance in the first principal component, possibly creating the illusion of order out of noise.

Summary Points and Conclusions

Ree et al.'s definition of a DGF is tautologous and subjective. By design, the first unrotated principal component will always explain a plurality of the variance in a correlation matrix. Whether the variables' loadings on the first principal component are nontrivial is, to some extent, in the eyes of

[2] $N = 50$ satisfies a widely accepted 10 to 1 subjects-to-variables ratio rule of thumb for sufficient sample size for factor analysis, although we do not recommend its invocation (see Bandalos & Boehm-Kaufman, 2009).

[3] These data are available from the second author.

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the beholder. The definition is operational, not theoretical, though we do appreciate Ree et al.'s speculations as to possible etiologies of DGFs. Still, as presented by Ree et al., DGFs are mathematical rather than theoretical constructions. As such, we question whether DGFs can be afforded equivalent theoretical, psychological interpretations across different construct domains and different levels of analysis. For example, general mental ability qua DGF can be considered a key individual difference characteristic that has biological, educational, nutritive, and other cultural determinants and is itself (in part) a determinant of more specific mental abilities and a wide variety of important life outcomes (Herrnstein & Murray, 1994). In a different domain, a general factor in assessment center performance is probably best and most parsimoniously understood as the tendency to perform generally well (or not so well) across all exercises and dimensions, itself influenced by factors such as General Mental Ability, Job Knowledge and Experience, Conscientiousness, and so on (Hoffman, Kennedy, LoPilato, Monahan, & Lance, 2015; Meriac, Hoffman, & Woehr, 2014). As such, DGFs in different construct domains necessarily have different conceptualizations and different nomological networks. Likewise, DGFs deeper in nomological networks (i.e., higher order factors such as general mental ability) will have broader explanatory power than will those that are closer to observed data (e.g., spatial ability). In brief, DGFs are easily found but, at least so far, not as well understood.

PCA is, by design, prone to discover DGFs and especially in small matrices of moderate to high correlations even if, as we showed earlier, there is no theoretical reason to expect one. PCA is an atheoretical variance decomposition technique that neither provides a unique representation of any data structure nor invites comparisons of alternative structures. Use of more modern modeling methods, such as generalizability theory (G-theory) and CFA, allows much more power and flexibility in this regard. For example, Putka and Hoffman (2013) and Hoffman, Melchers, Blair, Kleinmann, and Ladd (2011) have used G-theory and CFA, respectively, to test theoretically derived structures of assessment center data that include a general factor. These are just two examples in which theory of covariance structures can be translated into testable models of data—a component that is missing entirely in the analytic paradigm proposed by Ree et al.

Finally there is the issue of multidimensionality. As Ree et al. showed (and we replicated), a DGF can be found at the top of many multidimensional constructs' structures, though this is often not the focus of the original research. For $q = 3$ oblique first-order factors, it is mathematically arbitrary whether they are structured as simply correlated or dependent on a single second-order factor. For $q \geq 4$, these alternative structures represent alternative hypotheses that are testable using techniques such as hierarchical CFA

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but not PCA of the first-order factor correlations. A DGF may be supported as a second-order factor in many hierarchical CFAs but not in others. Either way, multidimensionality will continue to be ubiquitous at least at the level of first-order factors for many constructs.

In summary, (a) the criteria proposed for DGFs and the procedures proposed to detect them set a low bar for demonstrating the ubiquity of DGFs; (b) theory should be viewed as a necessary prerequisite guide to the analysis of covariance structures, including tests of the viability of DGFs; and (c) multidimensionality still reigns, at least at the level of first-order factors. Ree et al.'s proposal to extend the idea of a DGF beyond the cognitive realm is an intriguing concept but one that is not (yet) poised to be dominant in I-O psychology.

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Managing the First Factor: Context Is Important

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In the focal article, Ree, Carretta, and Teachout (2015) address a common error in research methods, in which researchers neglect the shared variance between facets of a multidimensional construct. We agree with the need to attend to the entire factor structure of constructs when using measures, whether in research or application. The objective of this commentary is to elaborate on useful practices when a dominant general factor (DGF), as defined by the focal article, is found to be present and, in particular, to explore cases of DGF results under research paradigms not considered by the focal article.

We hold, as a general principle, that particular data do not demand a particular analysis. Rather, particular data support many types of analyses. A method of analysis should be chosen so as to answer the research question, using only the data available and/or the data that can reasonably be collected.

That said, we agree that there is wisdom in doing an exploratory factor analysis or at least examining the matrix of correlations between scales and measures that are expected to constitute a multidimensional construct space. It may be the case that the scales are clearly differentiated by theory or by previous empirical studies; nevertheless, independence should not be assumed.

Beyond those general words, the specifics of the research context and the research question become relevant. In the context of test development, for example, application of a common factor model can be seen as a ma-

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