Journal of Clinical and Experimental Neuropsychology

ISSN: 1380-3395 (Print) 1744-411X (Online) Journal homepage: http://www.tandfonline.com/loi/ncen20

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To cite this article: Dennis J. McFarland (2012) A single g factor is not necessary to simulate positive correlations between cognitive tests, Journal of Clinical and Experimental Neuropsychology, 34:4, 378-384, DOI: 10.1080/13803395.2011.645018

To link to this article: http://dx.doi.org/10.1080/13803395.2011.645018

Published online: 20 Jan 2012.

JOURNAL OF CLINICAL AND EXPERIMENTAL NEUROPSYCHOLOGY
2012, 34 (4), 378–384

Psychology Press
Taylor & Francis Group

A single g factor is not necessary to simulate positive correlations between cognitive tests

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In the area of abilities testing, one issue of continued dissent is whether abilities are best conceptualized as manifestations of a single underlying general factor or as reflecting the combination of multiple traits that may be dissociable. The fact that diverse cognitive tests tend to be positively correlated has been taken as evidence for a single general ability or “g” factor. In the present study, simulations of test performance were run to evaluate the hypothesis that multiple independent abilities that affect test performance in a consistent manner will produce a positive manifold. Correlation matrices were simulated from models using either one or eight independent factors. The extent to which these factors operated in a consistent manner across tests (i.e., that a factor that facilitates performance on one test tends to facilitate performance on other tests) was manipulated by varying the mean value of the randomly selected weights. The tendency of both a single factor and eight independent factors to produce positive correlations increased as the randomly selected weights operated in a more consistent fashion. Thus the presence of a positive manifold in the correlations between diverse cognitive tests does not provide differential support for either single factor or multiple factor models of general abilities.

Keywords: Abilities; Simulation; Positive manifold.

Currently one of the principal arguments for the construct of general intelligence, or g, is the fact that a matrix of correlations between diverse cognitive tests can be described as a positive manifold (Carroll, 1993; Molenaar, Dolan, Wicherts, & van der Maas, 2010; Murphy, Dzieweczynski, & Zhang, 2009; Spearman, 1904). That is, correlations between tests of abilities tend to be positive. This positive manifold is generally thought to result from the operation of a common factor that influences performance on all tests of mental abilities. Alternative viewpoints hold that intelligence is best described as multiple independent abilities (e.g., Gardner, 1983; Guilford, 1972). However, in a survey of opinions, Reeve and Charles (2008) found that there seems to be a general consensus among experts that g is a valid construct.

The construct of a general factor accounting for a large portion of the variance in tests of cognitive abilities may be antithetical to the modular approach taken by most neuropsychologists (Anderson, 2005). There have been attempts at integration. For example, it has been suggested that the construct of psychometric intelligence is associated with the frontal lobes (Duncan, 2005). However this view contrasts with the description of frontal lobe function as fractionated (Stuss & Levine, 2002). Thus, the notion of a single general factor is at odds with the view of specific dissociable abilities that is common in neuropsychology.

There have been recent attempts to explain the positive manifold without recourse to g. Van der Maas et al. (2006) suggest that the positive manifold could result from multiple independent cognitive abilities that become correlated through a process of mutualism. Mutualism is described as a process of positive beneficial interactions between cognitive factors during development. Van der Maas

I thank Loretta S. Malta for her helpful discussions and comments on this manuscript.

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http://www.psypress.com/jcen http://dx.doi.org/10.1080/13803395.2011.645018

et al. (2006) demonstrate how this might occur by means of simulated test scores. Bartholomew, Deary, and Lawn (2009) discuss a bonds model derived from a proposal originally suggested by Thompson (1920) as a competing explanation for Spearman's (1904) observations. The bonds model posits multiple factors that are sampled by any given test score. Bartholomew (2007) showed that the Spearman (1904) and Thompson (1920) models are statistically indistinguishable.

A feature of the bonds model is that each of the independent factors (bonds) contribute to all test scores in the same way; that is, because a bond has a weight of either 0 or 1, if a bond affects test scores, it will always do so in a positive manner. Specifically, Bartholomew (2007) expressed this bonds model as

$$t = Wa \tag{1}$$

where t is a vector of test scores, W is a matrix of coefficients that describe whether a given bond has been sampled by a given test, and a is a vector of random values that describe individual differences in these bonds. (The notation has been changed but the model is identical to that discussed by Bartholomew, 2007.) Thus, if sampled by test i, larger values of a_i, the variable describing individual differences, always produce larger values of t_i, the variable representing test scores. If the probability of a bond being included on the ith test is p, then the mean value of the weights in W is equal to p and thus varies between 0 and 1. As a result, if a bond affects a test score, it is always in a positive manner, and thus the bonds model holds that individual differences operate in a consistent manner across tasks—that is, a bond will not have a negative effect on performance.

While the bonds model represents a case where a positive manifold can be produced without the need to postulate a general factor, it is a highly specific case since it assumes weighting on any given task of either 0 or 1. The notion that a specific ability has equivalent effects on all tasks that it influences is unlikely to be the case in practice. This assumption is not made in research on models of abilities, which generally estimate the weighing of each factor separately and find that the resulting estimates are not equal as would be predicted by the bonds model (e.g., Tulsky & Price, 2003). Furthermore, it is entirely possible that in some cases a given ability might actually be associated with poorer performance. Thus, a more general model that allows for a continuum of factor weights on different tests would have greater plausibility. Hence, in the present study, simulation was used to determine whether a positive manifold could be obtained from a set of uncorrelated abilities with weights that were continuous rather than binary.

The bonds model is a specific case of a more general condition in which individual differences affect performance in a relatively consistent manner across cognitive tasks. Given that a factor has a relatively consistent effect across a set of tests, its mean weight across tests will differ from zero. In contrast, if the values of the weights associated with a specific ability in W had a mean of zero and some standard deviation σ, then larger values of a would be expected to decrease performance on a given test as often as they increased performance. In this case, abilities would not operate in a consistent manner across tests (i.e., across tests, a given ability would decrease performance as often as it improved performance). In practice, it can be difficult to test this hypothesis without knowing the true extent to which individual differences affect performance. Simulation studies can fill this knowledge gap, because the effects of a factor or factors on test performance can be systematically manipulated by varying the mean value of the factor weights.

Sternberg (1979) describes two major approaches that have emerged in the study of mental abilities. The differential approach has primarily studied relationships between patterns of test scores within individuals, principally by means of factor analysis. The information-processing approach has primarily varied attributes of cognitive tasks, focusing on task attributes rather than subject attributes. Simulations of cognitive performance have been employed by the information-processing approach. Simulation has not been a favored method of the differential approach. However, simulation is a useful form of modeling that has shown great utility in modeling complex and otherwise intractable problems in physics (Rohrlich, 1990). It well might also prove useful in the biological and social sciences, including differential psychology.

Hence, the present study used simulations to examine the general conditions whereby a positive manifold could result from multiple uncorrelated latent abilities. The hypothesis is that a positive manifold results when these multiple abilities operate in a relatively consistent manner across diverse tasks. For example, we would expect an ability such as freedom from distraction to facilitate performance on most cognitive tests. While it might be more important for some cognitive tasks than others, in general, freedom from distraction should not have detrimental affects on test performance. Other abilities such as speed of information processing or memory would likewise tend to facilitate performance on most cognitive tests. While a different set of cognitive abilities might better explain human performance, this example illustrates how potentially uncorrelated abilities might be related. The essence of this view is that the effects of abilities/disabilities should have relatively consistent effects across tasks. This should be sufficient to produce a positive manifold.

In the present study, simulations of test performance were run to evaluate the hypothesis that multiple independent abilities that affect test performance in a consistent manner will produce a positive manifold. Weights of eight simulated abilities were randomly determined for 10 simulated tests. Sampled correlation matrices differed in the mean of the distribution of weights. The mean of the weight distributions determined the extent to which these simulated abilities affected performance in a consistent manner across tests. If the bias (i.e., mean) is 0, then the sampled weights for any given ability should vary about 0. Thus, on any test in the sample, the weights would be as likely to result in larger test scores as smaller test scores. However, if the mean of the distribution is nonzero, then the sampled weights would be more likely to have the same sign across simulated test scores. Thus a given ability should be more consistent in its effects across simulated tests as the bias increases. This simulation is a test of the hypothesis that consistency of the effects of latent factors across observed tests determines the extent to which a positive manifold is produced. Principal component analysis was done on each correlation matrix, as it is believed by some theorists that the size of the first eigenvalue is an index of g (e.g., Hartmann & Reuter, 2006; Jensen & Weng, 1994). If multiple uncorrelated factors can produce a positive manifold, then the well-established observation of positive correlations between diverse cognitive tasks does not provide exclusive support for a model of abilities based on a single general factor.

METHOD

Generation of simulated correlation matrices

Multiple correlation matrices were constructed from simulated test scores defined by random weights for latent factors that represent individual differences. New weights for tests were randomly drawn for each correlation matrix. New random values of the latent factors representing individual differences were drawn for each observation.

All simulations were done with SAS statistical software (SAS Institute Inc., Cary, NC). For each correlation matrix, a set of either 10 (for a single ability) or 80 (for eight abilities) ability weights were randomly generated using the output of the *normal* function from SAS and a constant offset, or bias. Here we refer to the latent factors representing individual differences as abilities rather than bonds. The SAS normal function produces a pseudorandom value from a normal distribution with a mean of 0 and a standard deviation of 1. Addition of the bias causes the distribution of sampled weights to have a mean approximating the value of the bias. As the mean of the distribution of weight values deviates more from zero, the weights tend to operate in a more consistent manner across simulated test scores. The resulting ability weights can be considered to be the contribution of either one or eight hypothetical abilities to 10 hypothetical test scores. Thus, for the ith test and jth ability,

$$w_{ij} = \frac{b + n_{ij}}{m} \tag{2}$$

where w_{ij} is the weight for the jth ability's contribution to the ith test, b is the bias, and n is a draw from the SAS random numbers generator. The sum of b and n was divided by m (an estimate of the mean of the absolute value of the sum of b and n_{ij}) to normalize the weights for each value of b, because adding a constant would tend to increase the absolute magnitude of the weights.

For each of the k (i.e., 2,000) observations per correlation matrix, the ability values were randomly generated using the output of the normal function. Each of 10 test scores was then computed by summing the products of the ability weights with the ability values and adding a random error term also drawn from the normal function. Thus, for the kth score on the ith test,

$$t_{ik} = \sum \left(w_{ij} \cdot a_{jk}\right) + e_{jk} \tag{3}$$

where a_{jk} is the magnitude of the jth ability for the kth observation, and e_{jk} is a random error term with a mean of 0 and a variance of 1. The sign of each w_{ij} for a give jth ability was also randomly selected for each correlation matrix with the normal function. Thus, for any given simulation, a factor tended to either consistently facilitate performance or consistently inhibit performance. It is important to note that the values of w_{ij} were constant across each correlation matrix, whereas the values of a_{jk} and e_{jk} changed with each observation. The first 10 simulated test scores were then used to generate a correlation matrix with the SAS CORR procedure.

Analysis of correlation matrices

One hundred correlation matrices were constructed for each bias value of 0, 0.6, 1.2, and 1.8. This was done for test scores simulated from either one or eight abilities. These correlation matrices were each individually analyzed with the principal component option of the SAS Factor procedure. The factor results and correlation matrices were then exported as files and were subsequently read into a custom program (written in C^{++}) to extract and organize the data. This output was then read back into SAS for analysis.

RESULTS

Characterizing the correlation matrixes

The most critical analysis of the present study pertained to examining the impact of the *bias* factor on the structure of the resulting correlation matrices. Table 1 presents a summary of means for each condition of the mean value of the correlations in each matrix, the minimum correlation in each matrix, and the maximum correlation in each matrix. Each tabled value is the mean from 100 simulated correlation matrices. As can be seen in Table 1, given a bias of 0, the mean correlation was 0 for both the simulations with one ability and the simulations with eight abilities. As the bias increased, the value of the mean correlation increased for both the matrices simulated from one ability and the matrices simulated from uncorrelated eight abilities. This effect was highly significant, as evaluated by analyses of variance (ANOVAs): $F(3, 396) = 649.38$, $p < .0001$, for one ability, and $F(3, 396) = 3{,}690.04$, $p < .0001$, for eight abilities. Similar effects were seen for minimum and maximum correlations. For the former, $F(3, 396) = 217.60$, $p < .0001$, for one ability, and $F(3, 396) = 1{,}469.03$, $p < .0001$, for eight abilities. For maximum correlations, $F(3, 396) = 124.40$, $p < .0001$, for one ability, and $F(3, 396) = 648.57$, $p < .0001$, for eight abilities. These results demonstrate that a positive manifold is not produced with either one ability or eight uncorrelated abilities when the mean of the weight distributions is 0. However, when the bias increased, the simulated abilities produced a positive manifold. This is the case with both one and eight independent abilities.

The correlation matrices produced by eight independent factors were also factored with the SAS Factor procedure using the default option of principal components and retention of factors with eigenvalues greater than 1.0. As can be seen in Table 2, this procedure never recovered all eight factors. In addition, with larger values of bias, often only one or two factors were recovered.

The average magnitude of the first eigenvalue produced with principal component analysis of

TABLE 1
Average mean, minimum, and maximum correlation of simulated matrices for one and eight uncorrelated abilities

		Correlation		
Absolute bias	*Number of abilities*	*Mean*	*Minimum*	*Maximum*
0.00	1	−.01	−.72	.73
0.00	8	.00	−.53	.52
0.60	1	.12	−.58	.78
0.60	8	.19	−.32	.62
1.20	1	.27	−.23	.75
1.20	8	.43	.08	.69
1.80	1	.66	.17	.93
1.80	8	.72	.43	.89

TABLE 2
Factors recovered by principal components with eigenvalue > 1 criteria as a function of bias

	Factors				
Bias	*1*	*2*	*3*	*4*	*5*
0	0	0	12	70	18
0.6	0	0	51	46	3
1.2	11	64	25	0	0
1.8	90	10	0	0	0

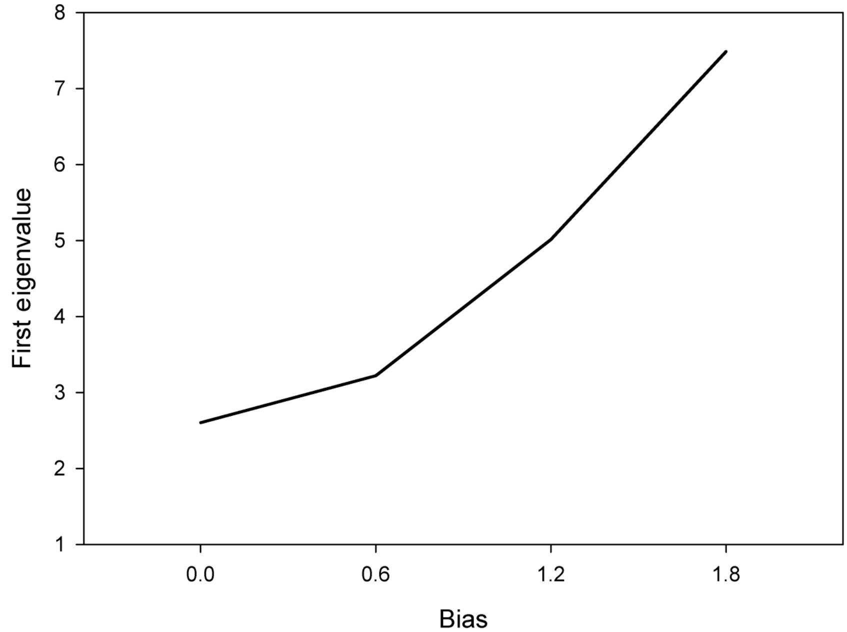

Figure 1. Average magnitude of the first eigenvalue produced by principal component analysis.

the eight factor matrices is shown in Figure 1. Larger average eigenvalues were produced as the bias increased, resulting in a significant main effect of bias, $F(3, 799) = 5{,}624.09$, $p < .0001$, as well as a significant main effect of method, $F(1, 799) = 177.55$, $p < .0001$, and the interaction between these terms, $F(3, 799) = 6.90$, $p < .0001$.

DISCUSSION

The present results show that a positive manifold can result from simulated test scores produced by either one or eight independent abilities. In both cases, a positive manifold requires that the underlying abilities operate in a consistent manner across simulated tests. Thus, the presence of a positive manifold does not represent clear evidence for g as proposed by a number of theorists (Carroll, 1993; Jensen, 1993; Spearman, 1904). Although selection of eight underlying ability dimensions is arbitrary, it does demonstrate the principle that multiple independent factors can generate a positive manifold.

As indicated by Equation 2, the weighting of abilities for each test within each simulated correlation matrix is a joint function of the bias and a random value. The sign of all of the weights for a given ability also randomly varies for each correlation matrix, so that overall these weights do not differ from zero. However, this bias manipulation influences the extent to which a given ability affects, in a consistent manner, each of the simulated test scores used to produce a given correlation matrix. These simulated weightings are constant across all of the cases that generate each correlation matrix. In contrast, the random ability variables described in Equation 3 vary with each case and thus represent individual differences. The primary finding of the present study is that multiple independent individual abilities (i.e., variables randomized on a case-wise basis) can produce a positive manifold.

There have been several other models that explain the positive manifold in tests of ability. Van der Maas et al. (2006) suggest that ability tests depend upon multiple cognitive factors that, while initially independent, interact during development to become interrelated. While this may be true, the present results show that multiple factors affecting cognitive test performance need not be correlated to produce a positive manifold. Bartholomew (2007) showed that Thompson's bonds model produces a correlation matrix indistinguishable from that produced by Spearman's model. The bonds model requires that any given ability be sampled by a given test with a weight of either 0 or 1. The present results show that abilities can have weights that take on a continuous range of values provided that they operate in a relatively consistent manner across cognitive tasks—that is, their weights tend to have the same sign on different tests. This must also be the case for a general factor to produce a positive manifold.

Finally, the present study shows that a common factoring procedure (i.e., principal components analysis with retention of eigenvalues greater than 1) never recovers the eight independent factors. As bias increased, fewer factors were recovered. In fact, at the largest value examined in these simulations, this analysis most often recovered only a single factor. While there are many different methods that might be employed in factoring a correlation matrix, these results point to a general trend where larger biases result in fewer recovered factors and larger values for the first eigenvalue. This is important since factor analysis was originally developed to identify g, and several theorists have suggested that the size of the first eigenvalue is in fact an index of g (e.g., Hartmann & Reuter, 2006; Jensen & Weng, 1994).

These simulations thus extend the results reported by Bartholomew et al. (2009) in showing that independent factors can produce a positive manifold without assuming binary weighting of factors and produce one or a few factors upon factor analysis. These points are important as data are already available that need to be accounted for by any model of the positive manifold. For example, multiple factor extraction criteria suggest one or two factor solutions for the Wechsler Adult Intelligence Scale (WAIS; Canivez & Watkins, 2010).

As pointed out by Bartholomew et al. (2009), differences between these models might be important for a neurophysiological and theoretical understanding of abilities. For example, neuroimaging (Lunders, Narr, Thompson, & Toga, 2009) and genetic (Davis et al., 2010) studies of abilities often correlate biological parameters with a global measure of cognitive ability. Alternative analyses aimed at identifying the biological correlates of more specific abilities could potentially have greater sensitivity and specificity.

Likewise, the assertion that most tests of frontal lobe function reflect g (Obonsawin et al., 2002) could simply be the result of a statistical analysis that uses as a covariate the sum of several tests measuring multiple independent abilities (i.e., the Wechsler Adult Intelligence Scale–Revised; WAIS–R). Statistical modeling that does not presuppose a single unitary factor might be more appropriate.

These results could also be applied to the domain of personality. For example, it has been proposed that there is a general factor of personality (e.g., Rushton & Irwing, 2009), and this could be explained by multiple independent factors operating in a relatively consistent manner across tests. These results might also help explain the existence of more specific factors of personality. For example, multiple independent factors might operate in a relatively consistent manner on various indices of traits such as emotional stability or consciousness. The possibility of multiple independent factors producing these traits may be somewhat intuitively obvious as traits like conscientiousness are likely to have similar determinants across different situations.

The multiple independent factors modeled in the present study differ from the manner in which human abilities are typically modeled. One approach models test performance as a composite of a single general ability and a single specific factor (e.g., Gignac, 2005). Another approach models test performance as being determined by a single group factor, with the group factors being correlated (e.g., Tulsky & Price, 2003). These two approaches are essentially equivalent. They tend to assume that performance on a given cognitive test is determined by one or a few underlying individual differences. The multidimensional model evaluated in the present study assumes that each cognitive test is influenced to a varying extent by all of the general abilities. Hybrid models are also conceivable, where a given cognitive test is determined by multiple general factors and multiple specific factors.

The notion that g is composed of multiple independent factors is by no means novel (e.g., Bartholomew et al., 2009; Kaufman et al., 2009; Kranzler & Jensen, 1991). The results of the present simulation do not prove that abilities are likely to be determined by multiple independent factors. Rather they show that the tendency for cognitive tests to be positively correlated does not necessarily imply the presence of a single underlying general factor. Thus the presence of a positive manifold does not provide differential support for models postulating either one single factor or those postulating multiple dissociable factors.

The use of simulation may represent a limitation of the present work. A formal proof such as that done by Bartholomew et al. (2009) might be more convincing, but it is not clear that this is possible without making simplifying assumptions that make the resulting model less plausible.

As noted by Sternberg and Grigorenko (2001), the best way to study intelligence is through converging operations. The present study employed a simulation paradigm to investigate one assumption essential to models of mental abilities and traits, the construct of a general or g factor. The main finding was that the simulation demonstrated that it is not necessary to have a simplifying assumption of equal test weights to produce a positive manifold from multiple independent abilities. The difference between these models probably becomes more important when identifying antecedents of intelligence, such as genetic factors, or the nature of disorders, such as specific learning disabilities. Future research in the domains of abilities testing should continue to employ a variety of converging operations and methods to further elucidate our understanding of how and why individuals differ in abilities and personality tendencies.

Original manuscript received 1 June 2011
Revised manuscript accepted 14 November 2011
First published online 20 January 2012

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