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# Finding the *g*-factor in brain structure using the method of correlated vectors

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**Abstract**

It is unclear whether brain mechanisms underlying human intelligence are distributed throughout the brain or mainly concentrated in the frontal lobes. Data are inconsistent possibly due, at least in part, to the different ways the construct of intelligence is measured. Here we apply the method of correlated vectors to determine how the general factor of intelligence (*g*) is related to regional gray matter and white matter volumes. This is a re-analysis of an earlier study showing regional gray matter and white matter volume is correlated to Full Scale IQ (FSIQ). However, it is well-known that FSIQ taps several cognitive abilities and skills in addition to *g*. The results now show that the *g* factor accounts for several but not all FSIQ/gray matter correlations distributed throughout the brain and these areas may differ for young and older adults.


*Keywords:* IQ; General intelligence; *g*; Correlated vectors; Voxel-based morphometry; Gray matter

Diverse neuroimaging techniques have identified numerous brain areas where there is a relationship between brain function or volume and psychometric measures of intelligence (Duncan et al., 2000; Frangou, Chitins, & Williams, 2004; Gignac, Vernon, & Wickett, 2003; Gong et al., 2005; Gray, Chabris, & Braver, 2003; Haier, 1993; Haier et al., 2003; Haier, Jung, Yeo, Head, & Alkire, 2004; Haier, Jung, Yeo, Head, & Alkire, 2005; Haier et al., 1988; Haier, Siegel, Tang, Abel, & Buchsbaum, 1992; Haier, White, & Alkire, 2003; Isaacs et al., 2004; Jung et al., 1999a, 2005; Lee et al., 2006; Prabhakaran, Smith, Desmond, Glover, & Gabrieliet, 1997; Risberg & Ingvar, 1973; Thompson et al., 2001; Vernon, Wickett, Gordon Bazana, & Stelmack, 2000; Wilke, Sohn, Bryars, & Holland, 2003). Although there are inconsistencies, most imaging studies show areas related to intelligence measures are distributed throughout the brain (see review by Jung and Haier, submitted for publication). There are differences of interpretation with respect to how much frontal areas may be involved. Some of the differences may derive from the wide range of cognitive tasks used during functional imaging studies. Structural imaging studies have the advantage of being task independent (Haier et al., 2004; Toga & Thompson, 2005). Other differences may result from age and sex differences (Haier et al., 2004, 2005).

It is also reasonable to assume that these different views derive, at least in part, from the way the construct of intelligence is measured. Here we apply a powerful

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analytic approach proposed by Jensen (1998), namely, the method of correlated vectors (MCV). This method tests whether the general factor underlying all cognitive measures (*g*) extracted from a battery of several diverse tests, is related to some variable X (external to the battery) such as regional brain volumes or cortical activation. The answer to this question is derived from the computation of the correlation between the elements in the column vector of the various tests' *g* loadings and the elements in the column vector of the tests' correlations with X. If there is a significant correlation, then X should be considered related to *g*.

The MCV relies on the fact that there is a theoretically informative distinction between intelligence in general (e.g. FSIQ) and general intelligence (*g*). The later was first described by Spearman (1904) and should be conceived as a "distillate of the common source of individual differences in all mental tests, *completely stripped of their distinctive features of information content, skill, strategy, and the like*" (Jensen, 1998, p. 74, emphasis added). It is widely accepted that the *g* factor is the core of intelligence: "*g* … is likely to be present, in some degree, in nearly all measures of cognitive ability. Furthermore, it is an important factor, because on average over many studies of cognitive ability tests it is found to constitute more than half of the total common factor variance in a test" (Carroll, 1997, p. 31).

While the scientific construct of general intelligence (*g*) rests on the correlations among test scores, intelligence in general rests on the summation of standardized mental test scores. However, the simple sum of various test scores cannot be considered the optimal measure of general intelligence (*g*), but rather a measure of intelligence in general. Intelligence in general means *g* plus several more specific cognitive abilities and skills. Typical IQ scores comprise a complex mixture of those abilities and skills (Colom, Abad, Garcia, & Juan-Espinosa, 2002). Although IQ scores have high *g*-factor loadings, IQ scores only approximate *g*. FSIQ and *g* factor scores are highly related. However, *g* factor scores are not a pure measure of the *g* factor of the test battery from which it was extracted. An individual's *g* factor score is calculated as a *g*-weighted mean of the individual's standardized scores on each of the subtests. Therefore, it is contaminated by other factors (and/or test specificity, see Jensen, 1998). It must be noted that in the analyses presented in this paper we are not treating *g* as a *g*-factor score, but as a vector.

Therefore, it is important to realize that the *g* factor is a theoretical construct that can be represented by several vehicles (psychometric tests or biological indices are some examples) yielding some measurements. The distinction between constructs, vehicles, and measurements, is especially important, given that the correlation between a given intelligence test and some variable X may or may not be attributed to the *g* component of that test (Jensen, 1998).

Although some neuroimaging studies have specifically tried to assess *g* (Duncan et al., 2000) most studies use single or quite general indices of intelligence in general derived from tests like the Raven Progressive Matrices Test or Full Scale IQ scores obtained from the Wechsler Intelligence Scales. To use the MCV, different *g* loaded tests (like the Wechsler subtests) must be used in the same study. Therefore, only neuroimaging studies that use multiple tests can be re-analyzed with the MCV. For example, Jensen (1998) reanalyzed the data collected by Haier et al. (1992). Their study measured the total brain's glucose metabolic rate after participants had taken the WAIS-R. They reported inverse correlations suggesting high psychometric intelligence scores were associated with low cerebral glucose use. Jensen (1998) applied the MCV and glucose metabolic rate was correlated with scores on each of the WAIS-R's subtests and the column vector defined by these correlations was correlated −.79 with the vector of the subtests' *g* loadings. The finding demonstrated that *g* is specifically related to glucose metabolic rate: the higher the *g* loading of the test, the greater its negative correlation with glucose metabolic rate, consistent with the authors' interpretation of intelligence related to brain efficiency (Haier et al., 1988).

In another example, the MCV was used with elementary cognitive tasks (ECTs). Nettelbeck and Rabbitt (1992) defined a *g* vector from the WAIS's subtests and created a second vector by correlating a composite measure of processing speed with each of the WAIS subtests. The Pearson correlation between both vectors was .95 (Spearman rank-order correlation = .72, $p < .01$). Therefore, it was concluded that *g* underlies the correlation between intelligence and processing speed.

As noted, structural brain imaging has the advantage of being task independent. Voxel-Based Morphometry (VBM), a recent methodological advance, uses algorithms to segment gray matter and white matter from structural MRIs (Ashburner & Friston, 2000, 2001; Good et al., 2001, 2002). This methodology is especially suited to find out regional brain variations in gray matter and white matter that show significant correlations with individual differences in intelligence. VBM has been applied in several recent studies. Haier et al. (2004) first used VBM in adults, identifying several brain areas distributed throughout the brain that correlated with individual differences in FSIQ. Specifically,