Chapter 3

Psychometric *g*: Definition and Substantiation

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The construct known as psychometric *g* is arguably the most important construct in all of psychology largely because of its ubiquitous presence in all tests of mental ability and its wide-ranging predictive validity for a great many socially significant variables, including scholastic performance and intellectual attainments, occupational status, job performance, income, law abidingness, and welfare dependency. Even such nonintellectual variables as myopia, general health, and longevity, as well as many other physical traits, are positively related to *g*. Of course, the causal connections in the whole nexus of the many diverse phenomena involving the *g* factor is highly complex. Indeed, *g* and its ramifications cut across the behavioral sciences—brain physiology, psychology, sociology—perhaps more than any other scientific construct.

THE DOMAIN OF *g* THEORY

It is important to keep in mind the distinction between *intelligence* and *g*, as these terms are used here. The psychology of intelligence could, at least in theory, be based on the study of one person, just as Ebbinghaus discovered some of the laws of learning and memory in experiments with $N = 1$, using himself as his experimental subject. *Intelligence* is an open-ended category for all those mental processes we view as *cognitive*, such as stimulus apprehension, perception, attention, discrimination, generalization, learning and learning-set acquisition, short-term and long-term memory, inference, thinking, relation eduction, inductive and deductive reasoning, insight, problem solving, and language.

The *g* factor is something else. It could never have been discovered with $N = 1$, because it reflects *individual differences* in performance on tests or tasks that involve any one or more of the kinds of processes just referred to as *intelligence*. The *g* factor emerges from the fact that measurements of all such processes in a representative sample of the general population are positively correlated with each other, although to varying degrees.

A *factor* is a hypothetical source of individual differences measured as a component of variance. The *g* factor is the one source of variance common to performance on all cognitive tests, however diverse. Factors that are common to only certain groups of tests that call for similar mental processes, or a particular class of acquired knowledge or skills, are termed *group factors*.

The *g* factor should be thought of not as a *summation* or *average* of an individual's scores on a number of diverse tests, but rather as a *distillate* from such scores. Ideally, it reflects only the variance that all the different tests measure in common. The procedure of "distillation" that identifies the common factor, *g*, is *factor analysis*, a class of mathematical algorithms developed following the invention of principal components analysis in 1901 by the statistician Karl Pearson (1857–1936) and of common factor analysis in 1904 by Charles Spearman (Jensen, 2000). These methods are now used in a great many sciences besides psychology, including quantum mechanics, geology, paleontology, taxonomy, sociology, and political science. Readers who want a brief introduction to the workings of factor analysis are referred to the tutorial articles by John B. Carroll (1979, 1983, 1997).

FACTOR MODELS

Factor analysis can represent the correlational structure of a set of variables in different ways, called factor *models*. Depending on the nature of the variables, certain models can represent the data better than some other models. Factor models fall into two main categories: *hierarchical* and *nonhierarchical*.

The simplest model represents Spearman's *two-factor theory* of abilities, in which each test variable reflects only two sources of true-score variance—a *general* factor (*g*) common to all of the variables in the analysis and a *specific* factor (*s*) peculiar to each test. A variable's *uniqueness* (*u*) (shown for each of the nine variables in Fig. 3.1) consists of the variable's specificity (*s*) and random measurement error (*e*). In this simplest model,

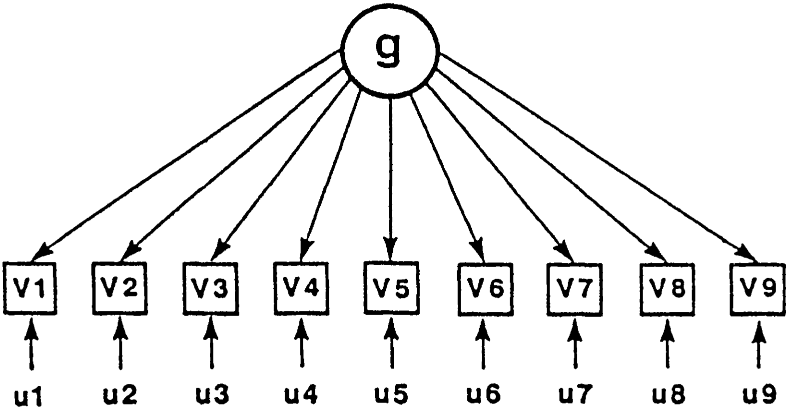

FIG. 3.1. The *two-factor model* of Spearman, in which every test measures only two factors: a general factor *g* that all tests of mental ability have in common and a factor *u* that is unique (or specific) to each test. From Jensen and Weng (1994). Used with permission of Ablex.

only one factor, *g*, accounts for all of the correlations among the variables. The correlation between any two variables is the product of their *g* factor loadings. Although it was seminal in the history of factor analysis, Spearman's model has usually proved inadequate to explain the correlation matrix of a large number of diverse tests. When *g* is statistically partialled out of the correlation matrix and many significant correlations remain, then clearly other factors in addition to *g* are required to explain the remaining correlations.

Burt (1941) and Thurstone (1947), therefore, invented multiple factor analysis. Illustrated in Fig. 3.2, it is not a hierarchical model. The three group factors (*F*1, *F*2, *F*3) derived from the nine variables are also called *primary* or *first-order* factors. In this illustration there is no general factor, only three independent (uncorrelated) factors, each comprising three intercorrelated variables. This model, originally hypothesized by Thurstone, didn't work out as he had hoped. Thurstone had believed that there is some limited number of independent primary mental abilities, so he *rotated* the factor axes in such a way as to make them uncorrelated with each other and to equalize as much as possible the variance accounted for by each of the factors, a set of conditions he referred to as *simple structure*. But this model never allowed a clear fit of the data, because every test battery he could devise, however homogeneous the item content of each of the diverse cognitive tests, always contained a large general factor. Though he tried assiduously to construct sets of uncorrelated tests, he found it absolutely impossible to construct mental tests that were not positively correlated with each other to some degree. In order to achieve a clean fit of the

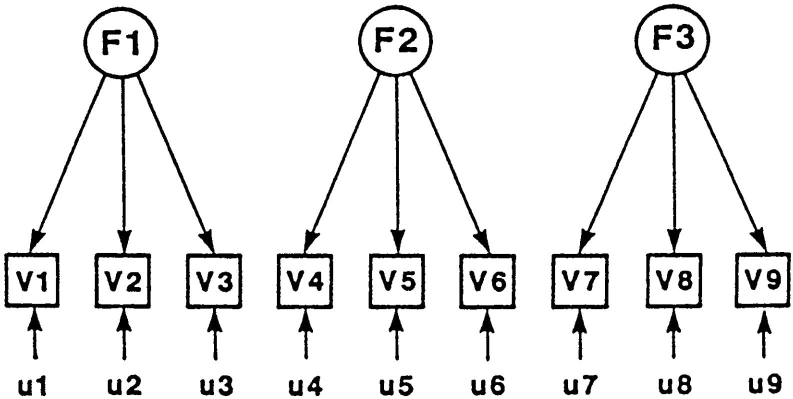

FIG. 3.2. The *multiple factor model* originally put forth by Thurstone (1887–1955), in which different sets of related variables (*V*) form a number of uncorrelated factors (*F*1, *F*2, *F*3, etc.). This model, therefore, has no general factor. From Jensen and Weng (1994). Used with permission of Ablex.

first-order factors to the separate clusters of tests, instead of orthogonal rotation of the axes he resorted to *oblique rotation* of the factor axes (i.e., the angle subtending any pair of axes is less than 90°), thereby allowing the first-order factors (e.g., *F*1, *F*2, *F*3) to be intercorrelated. The one factor common to these first-order factors, then, is a *second-order factor*, which is *g*. The first-order factors thus are *residualized*, that is, their common variance is moved up to the second-order factor, which is *g*. This is a hierarchical analysis, with two levels.

A nonhierarchical approach to multiple factor analysis that reveals the group factors as well as *g* was proposed by Karl Holzinger, one of Spearman's PhD students and later a professor at the University of Chicago. His bifactor model is now only one in a class of similar solutions called nested factor models. As shown in Fig. 3.3, a nested model first extracts the *g* factor (i.e., the first principal factor, which accounts for more of the total variance than any other single factor) from every variable, and then analyzes the residual common factor variance into a number of uncorrelated group factors. Note that there is no hierarchical dependency between *g* and the group factors in the nested model. Discussion of the nested model's theoretical and technical advantages and disadvantages as compared with the hierarchical model is beyond the scope of this chapter, but this has been nicely explicated elsewhere (Mulaik & Quartetti, 1997).

In the abilities domain, the *orthogonalized hierarchical model* has gained favor, especially with respect to identifying the same group factors across numerous different studies often based on different tests of the same basic abilities (Carroll, 1993). When a small matrix (fewer than 15 tests) is ana-

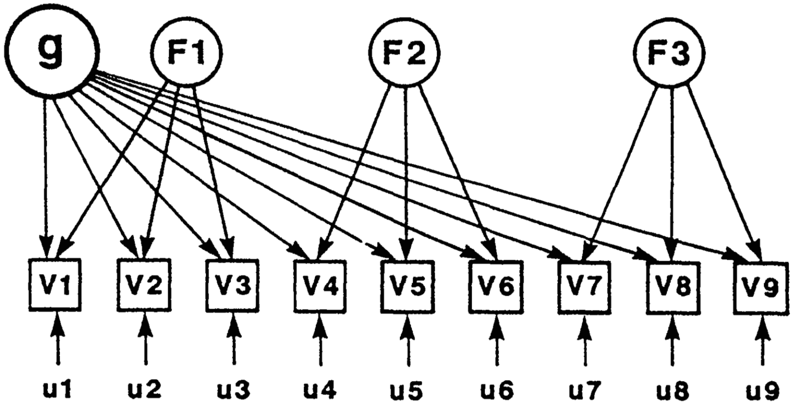

FIG. 3.3. A *nested multiple factor model,* which has a general factor *g* in addition to multiple factors *F*1, *F*2, etc. Holzinger's bifactor model was the first of this type of model. From Jensen and Weng (1994). Used with permission of Ablex.

lyzed the factor hierarchy usually has only two strata—the first-order factors and *g* appearing at the second order. When there is a large number of diverse tests there are many more first-order factors. When these are factor analyzed, they may yield as many as six to eight second-order factors, which then yield *g* at the third order.

Applying the hierarchical model to several hundred correlation matrices from the psychometric literature, Carroll (1993) found that *g* always emerges as either a second-order or a third-order factor. Inasmuch as *g* is ubiquitous in all factor analyses of cognitive ability tests, Carroll was more concerned with the identification of the other reliable and replicable factors revealed in the whole psychometric literature to date. He found about 40 first-order factors and 8 second-order factors, and, of course, the ubiquitous *g*. None of the hundreds of data sets analyzed by Carroll yielded any factor above a third-stratum *g*. He refers to the model that embraces these empirical findings as the "three-stratum theory" of human cognitive abilities.

A simple two-strata hierarchical analysis is illustrated in Fig. 3.4. The three first-order factors (*F*1, *F*2, *F*3) might be identified by the tests loaded on them, for instance, as verbal, numerical, and spatial ability factors. The numbers on the arrows are the *path coefficients* (correlations) between factors and variables at different levels of the hierarchy. A variable's *g* loading is the product of the path coefficients leading from the second-order factor (*g*) to the first-order factor (*F*), then to the variable (*V*). The *g* loading of V1, for example, is .9 × .8 = .72. The correlation between any two variables is the product of the shortest pathway connecting them. For exam-

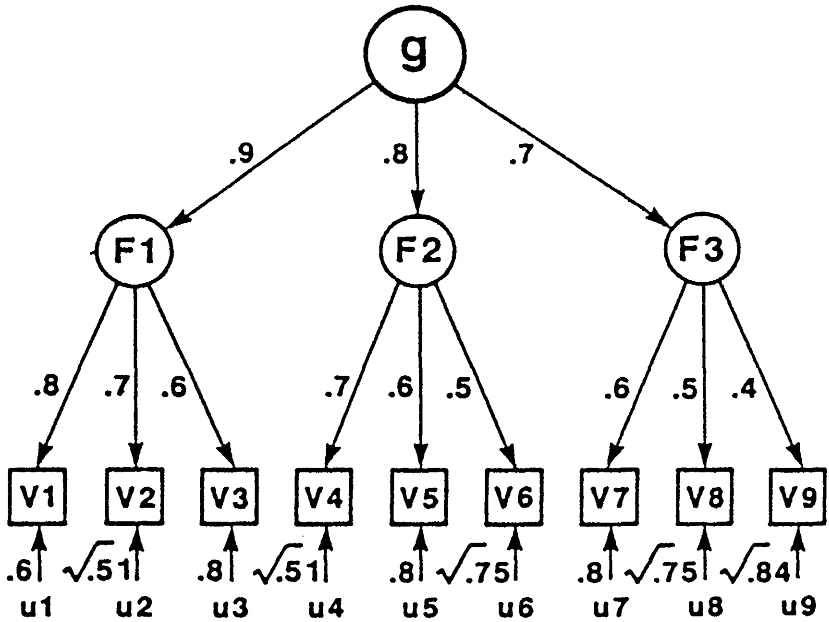

FIG. 3.4. A hierarchical factor model in which the group factors (*F*) are correlated, giving rise to the higher order factor *g*. Variables (*V*) are correlated with *g* only via their correlations with the group factors. The correlation coefficients are shown alongside the arrows. The *u* is a variable's "uniqueness" (i.e., its correlation with whatever it does not have in common with any of the other eight variables in the analysis). Reproduced from Jensen and Weng (1994) with permission.

ple, the correlation between *V*1 and *V*9 is $.8 \times .9 \times .7 \times .4 = .2016$. The factor structure is completely *orthogonalized*, apportioning the variance accounted for in each variable by *g* and by *F* independently by means of an algorithm known as the *Schmid-Leiman orthogonalization transformation*, which leaves all the factors that emerge from the analysis perfectly uncorrelated with one another (Schmid & Leiman, 1957). The final result is shown as a *factor matrix* in Table 3.1. The percent of the total variance accounted for by each factor is shown in the last row and the communality (h^2) of each variable is shown in the last column; it is the proportion of a single variable's total variance that is accounted for by all of the common factors in the set of variables subjected to the factor analysis. In this example, only 37.33% of the total variance in all of the variables is accounted for by the common factors, of which 68.1% is accounted for by *g*. The correlation between any two variables is the product of their *g* loadings plus the product of their loadings on the first-order factors.

TABLE 3.1
An Orthogonalized Hierarchical Factor Matrix

	Factor Loadings				
	2nd Order	*First Order*			*Communality*
Variable	g	F_1	F_2	F_3	h^2
V_1	.72	.35			.64
V_2	.63	.31			.49
V_3	.54	.26			.36
V_4	.56		.42		.49
V_5	.48		.36		.36
V_6	.40		.30		.25
V_7	.42			.43	.36
V_8	.35			.36	.25
V_9	.28			.29	.16
% Var.*	25.4	3.1	4.4	4.4	37.33

*Percent of total variance accounted for by each factor = the sum of the squared factor loadings. Besides g, which is common to all of the variables, there are three uncorrelated group factors (F_1, F_2, F_3).

HOW INVARIANT IS *g*?

An important question regarding *g* as a scientific construct is its degree of invariance. If *g* varied across different methods of factor analysis, or different batteries of diverse mental tests, or different populations, it would be of relatively little scientific interest. Although this question has not been studied as thoroughly as the importance of the subject warrants, the answers based on the most relevant data available at present indicate that *g* is indeed a remarkably stable construct across *methods*, *tests*, and *populations*.

Across Methods

Applying the 10 most frequently used methods of factor analysis (and principal components analysis) to the same correlation matrices, both for artificial data in which the true factor structure was perfectly known and for real data, it was found that every method yielded highly similar *g* factors, although some methods were in slightly closer agreement with the known true factor loadings than were others (Jensen & Weng, 1994). The mean correlation between *g* factor loadings was more than +.90, and the different *g* factor scores of the same individuals were correlated across the different methods, on average, +.99. It makes little practical or theoretical difference which method is used to estimate *g* for a given battery of tests. The group factors, however, are generally less stable than *g*.

Across Tests

Thorndike (1987) examined the stability of *g* across different test batteries by extracting a *g* factor by a uniform method from a number of nonoverlapping test batteries, each composed of six tests selected at random from a pool of 65 exceedingly diverse ability tests used in the U.S. Air Force. Included in each battery was one of the same set of 17 "probe" tests, each of them appearing once in each of the test batteries. The idea was to see how similar the *g* loadings of the probe tests were across the different batteries. The average correlation between the probe tests' *g* loadings across all the different test batteries was +.85. From psychometric principles it can be deduced that this correlation would increase asymptotically to unity as the number of tests included in each battery increased. This implies that there is a true *g* for this population of cognitive tests, of which the obtained *g* is a statistical estimate, just as an obtained score is an estimate of the true score in classical measurement theory.

Across Populations

Provided that all the subtests in a test battery are psychometrically suitable for the subjects selected from two or more different populations, however defined, the obtained *g* factor of the battery is highly similar across the different populations. By *psychometrically suitable* is meant that the tests have approximately the same psychometric properties such as similar reliability coefficients, absence of floor and ceiling effects, and quite similar correlations between each item and the total score (i.e., the *item-total correlation*). When such criteria of adequate measurement are met, the average congruence coefficient between the *g* loadings obtained from representative samples of the American Black and White populations in a wide variety of test batteries is +.99, or virtual identity (Jensen, 1998, pp. 99–100; 374–375). The same congruence coefficient is found between the *g* loadings of the Japanese on the Japanese version of the Wechsler Intelligence Scale subtests (in Japan) and the *g* loadings in the American standardization sample. Similar congruence is found in European samples (Jensen, 1998, pp. 85–86).

FLUID AND CRYSTALLIZED INTELLIGENCE (Gf AND Gc)

These terms and their symbols were coined by Spearman's most famous student, Raymond B. Cattell (1971). They emerge as group factors at the stratum just below *g*, as second-order factors. *Gf* is most highly loaded on nonverbal tests that call for novel problem solving (e.g., Wechsler Block

Designs, Raven's matrices, figural analogies), inductive reasoning, and short-term memory for newly learned material (e.g., the backward digit span test). *Gf* is aptly defined as what you use when you don't know what to do. It enters into new learning and solving novel problems for which the individual has not already acquired some specific algorithm, strategy, or skill for tackling the problem. Also, response times (RT) to elementary cognitive tasks (ECTs) that involve a simple decision (e.g., press the left-hand button when the red light goes on; press the right-hand button when the green light goes on) are typically more loaded on *Gf* than on *Gc*.

Gc is loaded in tests of acculturation and past acquired verbal and scholastic knowledge, general information, and problems for which individuals have prior learned relevant concepts and specific solution strategies (e.g., general information, vocabulary, arithmetic problems). *Gc* is especially characterized by the individual's having to draw on long-term memory for past-acquired information and skills.

In a homogeneous population with respect to education and cultural background, measures of *Gf* and *Gc* are always highly correlated. Along with other second-order factors, therefore, they give rise to the higher order factor *g*. In Cattell's *investment theory*, the correlation between *Gf* and *Gc* comes about because persons *invest Gf* in the acquisition of the variety of information and cognitive skills that constitute *Gc*, and therefore over the course of interacting with the total environment, those who are more highly endowed with *Gf* attain a higher level of *Gc*.

In a number of very large hierarchical factor analyses of a wide variety of tests where *g* is the highest-order factor and the group factors at lower levels in the hierarchy have been residualized (i.e., their *g* variance has been removed to the next higher stratum), the *Gf* factor disappears altogether. That is, its correlation with *g* is unity, which means that *g* and *Gf* are really one and the same factor (Gustafsson, 1988). The residualized *Gc* remains as a first-order or second-order factor, loading mainly on tests of scholastic knowledge and skill. Nevertheless, *Gc* is of great practical importance for a person's success in education, in employment, and in the specialized expertise required for success in every skilled occupation.

When a large collection of highly varied tests of crystalized abilities is factor analyzed, a general factor emerges that is much more like *g* than it is like *Gc*. It is obvious that *Gf*, *Gc*, and *g* are not clear-cut constructs and that Cattell's claim that he had split Spearman's *g* into two distinct factors is misleading. The generality of *g* is remarkably broad, with significant loadings in tests and tasks as disparate as vocabulary, general information, reaction time, and inspection time (Kranzler & Jensen, 1989; Vernon, 1989).

Because the ability to *acquire* new knowledge and skills (hence *Gf*) typically declines at a faster rate in later maturity than the *memory* of past acquired and well practiced knowledge and skills (hence *Gc*), the *Gf–Gc* distinction has proved most useful in studies of the maturation and aging of cognitive abilities. This increasingly important topic is beyond the scope of this chapter; references to the relevant literature are given elsewhere (Horn & Hofer, 1992).

THE EXTERNAL VALIDITY OF *g*

If the *g* factor were related only to purely psychometric variables, or were only a result of the way cognitive tests are constructed, or were solely an artifact of the mathematical procedures of factor analysis, it would be of little scientific or practical interest. But this, in fact, is not the case.

First of all, it should be known that a general factor is not a necessary characteristic of a correlation matrix, nor is it the inevitable result of any method of factor analysis. The empirical finding of positive correlations among all cognitive tests is not a methodological artifact, but an empirical fact. It has proved impossible to construct cognitive tests that reliably show zero or negative correlations with one another. In the personality domain, on the other hand, although there are a great many measures of personality and these have been extensively factor analyzed by every known method, no one has yet found a general factor in the personality domain.

Moreover, *g* is not a characteristic of only certain cognitive tests but not of others. If one examines the *g* loadings of all of a great many different mental ability tests in current use, it is evident that *g* factor loadings are a continuous variable, ranging mostly between +.10 and +.90, and the frequency distribution of all the loadings forms a fairly normal, bell-shaped curve with a mean of about +.60 and a standard deviation of about .15 (Jensen, 1998, pp. 380–383). Yet factor analysis has been used in the construction of very few of the most widely used IQ tests, such as the Stanford–Binet and the Wechsler scales. It so happens that IQ and other cognitive ability tests that are constructed to meet the standard psychometric criteria of satisfactory reliability and practical predictive validity are typically quite highly *g* loaded. And they are valid for a wide range of predictive criteria precisely because they are highly *g* loaded.

Spearman (1927) said that although we do not know the nature of *g*, we can describe the characteristics of the tests in which it is the most or the least loaded and try to discern their different characteristics. But that cannot tell us what *g* actually is beyond the properties of the tests and the operations of computing correlations and performing a factor analysis. Comparing the *g* loadings of more than 100 mental tests, Spearman characterized those with the largest *g* loadings as involving the "eduction of relations and correlates," or inductive and inductive reasoning, and as having the quality of "abstractness."

But it is not the tests themselves, but *g* as a major source or cause of individual differences in mental tests that is still not adequately understood, although we do know now that it involves more than just the properties of the tests themselves, because it is correlated with individual differences in a number of wholly nonpsychometric variables (Jensen, 1987, 1993b).

As for the tests themselves, and for many of the real-life tasks and demands on which performance is to some degree predictable from the most *g*-loaded tests, it appears generally that *g* is associated with the relative degree of *complexity* of the tests' or tasks' cognitive demands. It is well known that test batteries that measure IQ are good predictors of educational achievement and occupational level (Jensen, 1993a). Perhaps less well-known is the fact that *g* is the chief "active ingredient" in this predictive validity more than any of the specific knowledge and skills content of the tests. If *g* were statistically removed from IQ and scholastic aptitude tests, they would have no practically useful predictive validity. This is not to say that certain group factors (e.g., verbal, numerical, spatial, and memory) in these tests do not enhance the predictive validity, but their effect is relatively small compared to *g*.

The Method of Correlated Vectors

This is a method I have used to determine the relative degrees to which *g* is involved in the correlation of various mental tests with nonpsychometric criteria—variables that have no necessary relationship to mental tests or factor analysis. IQ tests and the like were never constructed to measure or predict these extrinsic variables, and the fact that IQ is found to be correlated with them is an informative phenomenon in its own right, suggesting that the tests' construct validity extends beyond the realm of psychological variables per se (Jensen, 1987; Jensen & Sinha, 1993). The key question posed by this finding is which aspects of the psychometric tests in terms of various factors or specific skills or informational content is responsible for these "unintended" correlations?

Two methods can be used to answer this question. The first is to include the nonpsychometric variable of interest in the factor analysis of the test battery and observe the factor or factors, if any, on which it is loaded and the relative sizes of its loadings on the different factors. This method requires that we have all of the measurements (including the extraneous variable) and all of their intercorrelations based on the same group of subjects.

The second method, *correlated vectors*, consists of obtaining the column vector of, say, the *g* factor loadings on each of the tests in a battery (e.g., the first column [*g*] in Table 3.1) and correlating the factor loadings with a parallel column vector consisting of each test's correlation with the external variable. The size of the correlation is an index of the relative degree (as compared with other tests in the battery) to which *g* (or any given factor) enters into the test's correlation with the external variable. The advantage of the correlated vectors method is that the factor loadings and the tests' correlations with the external variable need not be based on one and the same subject sample. It is often preferable to use factor loadings based on the test battery's standardization sample, which is usually larger and more representative of the general population than is the data set of any single study. Hence data reported in the literature that show various tests' correlations with some external variable but were never intended to relate the external variable to *g* or other common factors in the test battery can be used for the correlated vectors analysis even if a factor analysis of the tests (not including the external variable) has to be based on a different subject sample, for example, the standardization sample of the Wechsler Adult Intelligence Scale.

An example of correlated vectors is shown in Fig. 3.5, based on a study of the habituation of the brain's evoked electrical potentials (Schafer, 1985). Subjects sit in a reclining chair in a semidarkened room and hear a series of 50 "clicks" at 2-second intervals, while the amplitude of the brain's change in electrical potential evoked by the click is measured from an electrode attached to the vertex of the subject's scalp and is recorded on an electroencephalograph. In normal subjects, the amplitude of the evoked brain wave gradually decreases over the course of the 50 clicks. The rate of this decrease in amplitude is an index of the *habituation* of the brain's response to the auditory stimulus. In a group of 50 young adults with IQs ranging from 98 to 142, the habituation index correlated +.59 with the WAIS Full Scale IQ. But what is the locus of this correlation in the factor structure of the 11 WAIS subtests? We see in Fig. 3.5 that the various subtests' *g* loadings predict the subtest's correlations with the evoked potential habituation index with a Pearson $r = 0.80$ and a Spearman's rank-order correlation $\rho = 0.77$. Because the differing reliabilities of the various subtests affect both their *g* loadings and their correlations with the habituation index, it is necessary statistically to remove the effect of correlated errors in the *variables*' *g* loadings and in their correlations with the habituation index. (The procedure of correlated vectors and its statistical variations are explicated in detail in Jensen, 1998, Appendix B.) After the *g* factor was statistically partialled out of the 11 subtests, none of them showed a significantly non-zero correlation with the habituation index; *g* was the sole factor responsible for the correlation between the WAIS IQ and the habituation of the evoked potential.

The same kind of correlated vectors analysis as illustrated earlier has been used to determine whether a number of different genetic, chronometric, anatomic, and physiological variables are related to the *g* load-

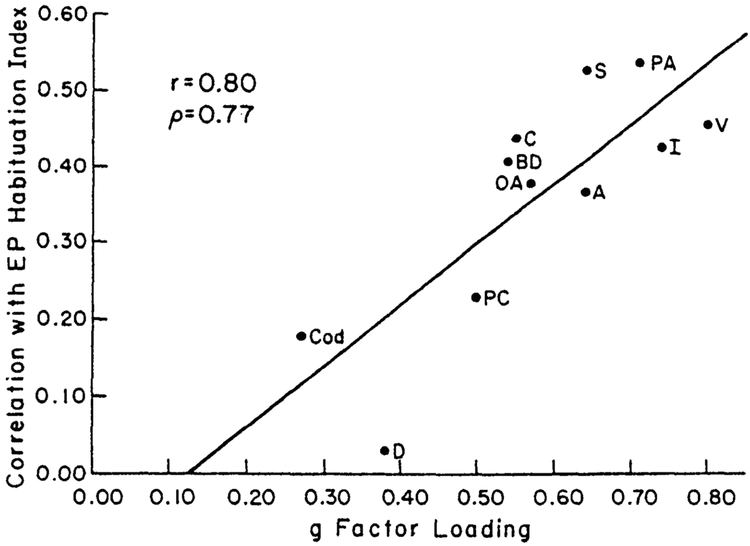

FIG. 3.5. Scatter diagram showing the Pearson correlation (*r*) and the Spearman rank-order correlation (ρ) between the correlations of each of the 11 subtests of the Wechsler Adult Intelligence Scale with the evoked potential (EP) Habituation Index (on the vertical axis) and the subtests' loadings on the *g* factor. The subtests are V–Vocabulary, PA–Picture Arrangement, S–Similarities, I–Information, C–Comprehension, BD–Block Designs, OA–Object Assembly, PC–Picture Completion, Cod–Coding, D–Digit Span. From Jensen (1998) with permission of Praeger.

ings in different batteries of mental tests, including the Wechsler scales. These are listed below, with the typical vector correlations shown in parentheses. Details of these studies are provided elsewhere (Jensen, 1998, chaps. 6–8).

- *Assortative mating* correlation between spouses' test scores (.95).
- The genetic *heritability* of test scores (.70).
- *Inbreeding depression* of test scores in offspring of cousin matings (.80).
- *Heterosis*-outbreeding elevation of test scores in offspring of interracial mating (.50).
- *Reaction time* (RT) on various elementary cognitive tasks (ECTs) (.80).
- *Intraindividual variability in RT* on ECTs (.75).
- *Head size* as a correlated proxy for brain size (.65).
- *Brain evoked potentials*: habituation of their amplitude (.80).
- *Brain evoked potentials*: complexity of their waveform (.95).

- *Brain intracellular pH* level; lower acidity → higher *g* (.63).
- *Cortical glucose metabolic rate* during mental activity (–.79).

It is a fairly certain inference that *g* is also mainly responsible for the simple correlation between scores on highly *g* loaded tests, such as standard IQ tests, and a number of other brain variables: brain volume measured *in vivo* by magnetic resonance imaging (MRI); brain wave (EEG) coherence; event related desynchronization of brain waves, and nerve conduction velocity in a brain tract from the retina to the visual cortex (Jensen, 1993b, 1997, 1998). There are also many physical variables that have less clearly brain-related correlations with IQ, such as stature, myopia, body and facial symmetry, blood chemistry, and other odd physical traits that somehow became enmeshed with the more direct neural and biochemical causes of individual differences in mental abilities in the course of human evolution or in ontogenetic development (Jensen & Sinha, 1993).

The functional basis of how and why all these physical variables are correlated with *g* is not yet known. The explanation for it in causal rather than merely correlational terms is now the major research task for the further development of *g* theory. Some of the as yet inadequately investigated and unproved hypotheses that have been put forth to explain the relationship of *g* to brain variables involve the total number of neurons, the number of connections between neurons (dendritic arborization), nerve conduction velocity, the degree of myelination of axons, the number of glial cells, and brain chemistry (neurotransmitters, ionic balance, hormonal effects, and so on).

The *g* factor at the level of psychometrics is now well established. Discovering its causal explanation, however, obviously requires that investigation move from psychology and psychometrics to anatomy, physiology, and biochemistry (Deary, 2000). This is now made possible by the modern technology of the brain sciences and will inevitably lead to the kind of reductionist neurophysiological explanation of *g* envisaged by its discoverer, Spearman (1927) who urged that the final understanding of *g* ". . . must come from the most profound and detailed direct study of the human brain in its purely physical and chemical aspects" (p. 403).

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