to the "obviousness" of a test—the degree to which the purpose of the test is apparent to those taking it. Tests wherein the purpose is clear, even to naïve respondents, are said to have *high face validity*; tests wherein the purpose is unclear have *low face validity* (Nevo, 1985). The concept of face validity is similar to *item subtlety*, but there are important differences as well. Whereas face validity describes the transparency of an entire test, item subtlety describes the transparency of individual test items (Bornstein, Rossner, Hill, & Stepanian, 1994). It is possible to construct a test wherein the purpose of individual test items is not apparent, but when these items are scrutinized as a group, the purpose of the test as a whole becomes obvious.

Face validity has contrasting effects on different types of tests. Studies indicate that high face validity can facilitate performance on intelligence, aptitude, and achievement tests: When the purpose of the test seems clear, testees are less anxious and more motivated to persevere, even when test items are highly challenging (Messick, 1995; Nevo, 1985).

High face validity can be a liability when a test is designed to assess some aspect of personality or psychopathology. In this situation, high face validity enables respondents to bias their responses to present themselves as they want to be seen by the examiner. Studies show that naïve respondents are able to "fake good" and "fake bad" more effectively on tests with high face validity than those with low face validity (Bornstein, 2002; Bornstein et al., 1994).

There are two general methods for evaluating the face validity of a test. Some psychometricians have taken a direct approach, asking participants to identify the purpose of an assessment instrument from among an array of likely choices. To the degree that participants can do this accurately, the test has high face validity. Other researchers have taken an indirect approach, asking participants to deliberately bias their answers to raise or lower their scores on the test. To the degree that participants can alter their scores in this way, the test is presumed to have high face validity and to be susceptible to self-presentation effects in vivo (Bornstein, 2002).

Given its importance for psychological tests, face validity should always be assessed and controlled during test development. Several strategies are useful. For example, test items can be worded subtlely, so the true purpose of the measure is masked. Alternatively, test items can be ordered so that those from a given subscale do not appear in proximity to each other; this has also been shown to lower the face validity of the test. Finally, distracter items unrelated to the true purpose of the test can be included so that the content of genuine test items is less obvious. This latter strategy is particularly effective, when combined with the other two approaches, for disguising the purpose of the test.

—Robert F. Bornstein

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FACTOR ANALYSIS

In general, the term *factor analysis* refers to any one of a number of similar but distinct multivariate statistical models that model observed variables as linear functions of a set of LATENT or hypothetical variables that are not directly observed, known as *factors.*

Factor analysis models are similar to REGRESSION models in that they possess DEPENDENT VARIABLES that are linear functions of INDEPENDENT VARIABLES. But unlike regression, the independent variables of the factor analysis models are not observed independently of the observed dependent variables.

Factor analysis models may be further distinguished according to whether the factor variables are determinate or not. Factors are determinate if they can be derived in turn as linear functions of the observed variables. Otherwise, they are indeterminate. Determinate models encompass the various component analysis models, such as PRINCIPAL COMPONENTS ANALYSIS (Hotelling, 1933; Joliffe, 1986; Pearson, 1901); weighted principal components (Mulaik, 1972); and Guttman's image analysis (Guttman, 1953). Indeterminate models are represented by the common factor model (Spearman, 1904; Thurstone, 1947), which seeks to account for the covariation between the observed variables as the result of the observed variables' sharing in varying degrees the influences of the variation of a common set of common factor variables.

Determinate factor analysis models are often useful in a data reduction role by finding a smaller number of variables that capture most of the information of variation and covariation among the observed variables. Scores on the determinate factors can be computed as linear combinations of the observed variables. These factor scores may be used as independent and dependent variables—as the case warrants—in other multivariate statistical procedures, such as multivariate regression or multivariate analysis of variance. However, for substantive theoretical work, the main drawback of these determinate component analysis models is that their factors represent statistical artifacts unique to the set of observed variables determining them (Mulaik, 1987). Change the set of observed variables, and you obtain different linear combinations. The component factors have no independent existence apart from the set of observed variables of which they are linear combinations.

In contrast, the common factors of the common factor model are indeterminate from the observed variables and are not linear combinations of them. Common factors can correspond to variables having an independent existence, and, in the theory of simple structure in common factor analysis (Thurstone, 1947), different sets of observed variables from a domain can be linear functions of the same common factors. Thus, for the purposes of discovering autonomous variables that have theoretical import as common causes of other variables, the common factor model is generally preferred to a determinate component analysis model.

However, the common factor model has limits to its application. Common factor analysis is limited to the case where there is no natural order among the observed variables. The only ordering principle permitted by the common factor model is the relation of functional dependency of observed variables on latent variables. No provision exists in the common factor model for functional dependencies between latent variables. Relations between latent variables only take the form of correlations or covariances, which are nondirectional and nonordering. But variables that are naturally ordered in time, space, or degree of some attribute may be more correlated with the variables immediately adjacent to them and have diminishing correlations with variables farther from them in the natural ordering. In these cases, in addition to functional dependencies of observed variables on latent variables, each successive latent variable corresponding to one of the observed variables in the order may be a linear function of only the immediately preceding latent variable in the order plus some new latent variable unique to it. Models with this property are known as simplex models (Jöreskog, 1979). To deal with this and other cases, STRUCTURAL EQUATION MODELING is more appropriate because it has provisions for establishing linear functional relations between latent variables. Thus, if one is to apply the common factor model properly to a set of observed variables, one must take care to determine at the outset that there is no apparent natural ordering among the variables. Although the common factor model may fit well to such data with a small number of common factors, the factors will usually defy theoretical interpretation (Jones, 1959).

Factor analysis models also can be distinguished as to whether they are exploratory or confirmatory. Exploratory common factor analysis is principally analytic, used in situations where there is minimal knowledge of the constituent factor variables of a domain of variables believed to conform to the common factor model. The aim is to analyze the observed variables to "discover" constituent variables that are more basic. Confirmatory factor analysis is principally synthetic. It is used where there is sufficient knowledge to formulate hypotheses as to how certain theoretical variables function as factors common to a number of observed variables. The theory allows one to predict within certain constraints the pattern of covariances among the observed variables and to test for this pattern (see CONFIRMATORY FACTOR ANALYSIS). The rest of this article will be about exploratory common factor analysis.

EQUATIONS OF EXPLORATORY FACTOR ANALYSIS

The equations of factor analysis are usually expressed in matrix algebra. Thus, the model equation of common factor analysis is given by the following matrix equation:

$$\mathbf{Y} = \mathbf{\Lambda X} + \mathbf{E},$$

where $\mathbf{Y}$ is a $p \times 1$ column vector of p observed random variables; Λ is a $p \times m$ matrix of factor pattern loadings λ_{ij}, which are analogous to regression coefficients; $\mathbf{X}$ is an $m \times 1$ column vector of common factor random variables; and $\mathbf{E}$ is a $p \times 1$ column vector of p unique factor random variables.

One then assumes the following: (a) The common and unique factor variables are uncorrelated, that is, $\text{cov}(\mathbf{X}, \mathbf{E}) = 0$; and (b) the unique factors are mutually uncorrelated, that is, $\text{cov}(\mathbf{E}) = \boldsymbol{\Theta}^2 =$ a diagonal matrix.

From the model equation and these assumptions, we are able to derive the fundamental theorem of the common factor model, expressed as

$$\text{cov}(\mathbf{Y}) = \boldsymbol{\Sigma} = \boldsymbol{\Lambda\Phi\Lambda}' + \boldsymbol{\Theta}^2,$$

where $\boldsymbol{\Sigma}$ is the $p \times p$ variance-covariance matrix for the p observed variables, $\boldsymbol{\Lambda}$ is the $p \times m$ factor pattern matrix of elements λ_{ij}, $\boldsymbol{\Phi}$ is the $m \times m$ matrix of VARIANCES and COVARIANCES among the common factors, and $\boldsymbol{\Theta}^2$ is a $p \times p$ diagonal matrix of unique factor variances. Because $\boldsymbol{\Theta}^2$is a diagonal matrix with zero off-diagonal elements, the off-diagonal elements of the covariance matrix $\boldsymbol{\Sigma}$ are due only to the off-diagonal elements of $\boldsymbol{\Lambda\Phi\Lambda}'$, which is a function of only the common factor variables.

Table 1 Fifteen Bipolar Personality Rating Scales Used to Produce 15 Variables for the Factor Analysis Study

1.	FRIENDLY:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNFRIENDLY
2.	SYMPATHETIC:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNSYMPATHETIC
3.	KIND:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:CRUEL
4.	AFFECTIONATE:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNAFFECTIONATE
5.	INTELLIGENT:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNINTELLIGENT
6.	CAPABLE:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:INCAPABLE
7.	COMPETENT:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:INCOMPETENT
8.	SMART:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:STUPID
9.	TALKATIVE:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNTALKATIVE
10.	OUTGOING:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:WITHDRAWN
11.	GREGARIOUS:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:SOLITARY
12.	EXTRAVERTED:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:INTROVERTED
13.	HELPFUL:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNHELPFUL
14.	COOPERATIVE:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNCOOPERATIVE
15.	SOCIABLE:	_1_:_2_:_3_:_4_:_5_:_6_:_7_	:UNSOCIABLE

STEPS IN PERFORMING A FACTOR ANALYSIS: A WORKED EXAMPLE

Step 1: Choosing or Constructing Variables

It is best to select or construct variables representing some domain of activity in a systematic manner. L. L. Thurstone (1947), a pioneer in the field of factor analysis, believed that a domain of variables is defined by the common factors that span it. Thus, one must consider the possible common factors that might exist in the domain. Then, for each of those anticipated factors, one should select or construct at least four indicator variables that one believes are relatively pure measures of those factors. Four indicators of an anticipated factor overdetermine the factor.

As an example, Carlson and Mulaik (1993) selected 15 variables based on 15 bipolar personality rating scales shown in Table 1 that they expected would represent four factors of personality: (a) friendliness, represented by the bipolar rating scales friendly-unfriendly, sympathetic-unsympathetic, kind-unkind, and affectionate-unaffectionate; (b) ability, represented by the scales intelligent-unintelligent, capable-incapable, competent-incompetent, and smart-stupid; (c) extraversion, represented by talkative-untalkative, outgoing-withdrawn, gregarious-solitary, extraverted-introverted, and sociable-unsociable. They anticipated that variables such as helpful-cooperative and cooperative-uncooperative would be concepts representing a combination of friendliness and ability, and would have "loadings" on these factors plus loadings on (d) an additional factor unique to them alone.

Step 2: Obtaining Scores on Variables and Computing Correlation Matrix

Carlson and Mulaik (1993) then had 280 students rate randomly selected descriptions of people in a work setting on the 15 rating scales. The correlations among the 15 scales were then obtained and are given in Table 2.

Step 3: Determining Number of Factors

The extraction of factors is based on the matrix of correlations between factors. However, a decision must be made at this point as to which method of factor extraction to use to find the estimates for the factor pattern coefficients, the correlations among the common factors, and the unique factor variances, which will be the basis for the ultimate interpretation of the analysis. The program used to perform this analysis was SPSS FACTOR Version 4.0 for the Macintosh

Table 2 Correlations Among 15 Variables

SYMMETRIC MATRIX
LOWER HALF SHOWN

	1 FRIENDLY	2 SYMPATHETIC	3 KIND	4 AFFECTIONATE	5 INTELLIGENT	6 CAPABLE	7 COMPETENT	8 SMART	9 TALKATIVE	10 OUTGOING	11 GREGARIOUS	12 EXTRAVERTED	13 HELPFUL	14 COOPERATIVE	15 SOCIABLE
1 FRIENDLY	1.000														
2 SYMPATHETIC	.777	1.000													
3 KIND	.809	.869	1.000												
4 AFFECTIONATE	.745	.833	.835	1.000											
5 INTELLIGENT	.176	.123	.123	.112	1.000										
6 CAPABLE	.234	.159	.205	.183	.791	1.000									
7 COMPETENT	.243	.155	.187	.186	.815	.865	1.000								
8 SMART	.234	.190	.238	.215	.818	.841	.815	1.000							
9 TALKATIVE	.433	.319	.321	.435	.174	.209	.239	.258	1.000						
10 OUTGOING	.473	.480	.410	.527	.220	.274	.269	.261	.744	1.000					
11 GREGARIOUS	.433	.438	.406	.526	.188	.227	.242	.228	.711	.853	1.000				
12 EXTRAVERTED	.447	.396	.350	.500	.192	.221	.227	.224	.758	.846	.801	1.000			
13 HELPFUL	.649	.693	.697	.694	.283	.344	.370	.365	.443	.552	.514	.473	1.000		
14 COOPERATIVE	.662	.692	.676	.679	.311	.345	.375	.351	.431	.557	.514	.493	.740	1.000	
15 SOCIABLE	.558	.543	.510	.632	.213	.289	.287	.287	.745	.886	.820	.830	.631	.626	1.000

computer. (Later versions are essentially unchanged in these options.) The program offers several methods of factor extraction appropriate for a common factor analysis. These are principal axis factoring, which is essentially unweighted least squares; unweighted least squares (a slightly different ALGORITHM for the same result); GENERALIZED LEAST SQUARES; and MAXIMUM LIKELIHOOD. All of these methods of extraction are iterative and require that an initial decision be made as to the number of factors to extract, because this number must be fixed at this value throughout the iterations. SPSS computes a principal components analysis with every factor analysis and displays the EIGENVALUES of the unmodified CORRELATION matrix R. These can be used to estimate the number of common factors. This is done by means of a SCREE PLOT, which is a plot of the magnitude of each of the eigenvalues against its ordinal position in the descending series of eigenvalues. Connecting the dots in this plot reveals a large first eigenvalue much higher than the rest, followed by a number of lesser eigenvalues of still substantial magnitude. But there is usually a point where the rapid descent in magnitude of the eigenvalues suddenly changes to a gradual, almost linear descent for the remainder of the eigenvalues. Many believe that this is in the vicinity of the point where the variables begin to be influenced by common factors in a significant way, and so this number is used as the number of common factors to extract. Others retain only so many factors as there are eigenvalues of R greater than 1.00. But this is well known to be a weakest lowest bound for the number of common factors. There may be more of lesser influence.

This and subsequent versions of SPSS FACTOR do not report a different set of eigenvalues that would be more revealing theoretically as to the number of common factors. Given the equation of the fundamental theorem of factor analysis above, we may substitute $\mathbf{R}$ for $\boldsymbol{\Sigma}$ to represent a correlation matrix. Guttman (1954, 1956) showed that a strong lower bound to the number of common factors would be the number of positive eigenvalues of the matrix $\mathbf{R} - \mathbf{S}^2$ where $\mathbf{S}^2 = [\text{diag}\mathbf{R}^{-1}]^{-1}$. $\mathbf{S}^2$ is a strong upper-bound approximation to $\boldsymbol{\Theta}^2$. This number of positive eigenvalues, however, is often on the order of $p/2$. Furthermore, many of the eigenvalues of $\mathbf{R} - \mathbf{S}^2$ are quite small, near zero, and so many researchers would like to examine a plot of these eigenvalues to determine a point at which the eigenvalues begin to assume substantial values. Developments by Harris (1962) that were adopted by Jöreskog (1967) in developing an algorithm for performing maximum likelihood factor analysis suggested that one could pre- and postmultiply $\mathbf{R} - \mathbf{S}^2$ by $\mathbf{S}^{-1}$ to obtain $\mathbf{S}^{-1}(\mathbf{R} - \mathbf{S}^2)\mathbf{S}^{-1} = \mathbf{S}^{-1}\mathbf{R}\mathbf{S}^{-1} - \mathbf{I}$. This transformation does not change the number of positive eigenvalues of the resulting matrix, so the number of positive eigenvalues of this matrix would equal the number of factors to retain. But each of the eigenvalues of this matrix would correspond to an eigenvalue of the matrix $\mathbf{S}^{-1}\mathbf{R}\mathbf{S}^{-1}$ minus 1. So, any eigenvalue greater than 1.0 of $\mathbf{S}^{-1}\mathbf{R}\mathbf{S}^{-1}$ would correspond to a positive eigenvalue of $\mathbf{S}^{-1}\mathbf{R}\mathbf{S}^{-1} - \mathbf{I}$. Thus, researchers could also profit from examining the eigenvalues of $\mathbf{S}^{-1}\mathbf{R}\mathbf{S}^{-1}$ to determine the number of common factors to retain.

A separate calculation in this example of the eigenvalues of $\mathbf{S}^{-1}\mathbf{R}\mathbf{S}^{-1}$ revealed only 7 of the

15 eigenvalues were greater than 1.00. These were 37.484, 14.467, 9.531, 1.436, 1.289, 1.116, and 1.065. Although three factors would be substantial in contribution, we will take one more because that was the theoretical expectation, and those beyond it would have a much smaller contribution (if you subtract one from each).

Step 4: Extraction of the Unrotated Pattern Matrix

The method of factor extraction used in this example was maximum likelihood. It is relatively robust, even when the variables do not have a multivariate normal distribution, and maximizes the determinant of the partial correlation matrix among the variables with the common factors partialed out, regardless of the form of the distribution. In this case, the estimate of the unrotated factor pattern matrix is given by $\hat{\mathbf{\Lambda}} = \hat{\mathbf{\Theta}}\mathbf{A}_m[\gamma_i - 1]_m^{1/2}$, where $\hat{\mathbf{\Theta}}$ is the square root of the iteratively estimated diagonal unique variance matrix, $\mathbf{A}_m$ is the $p \times m$ matrix whose columns are the first m eigenvectors of $\hat{\mathbf{\Theta}}^{-1}\mathbf{R}\hat{\mathbf{\Theta}}^{-1}$, and $[\gamma_i - 1]_m$ is a diagonal matrix of order m whose diagonal elements are formed by subtracting 1 from each of the first m largest eigenvalues γ_i of $\hat{\mathbf{\Theta}}^{-1}\mathbf{R}\hat{\mathbf{\Theta}}^{-1}$. In this solution, the common factors are mutually uncorrelated. But the unrotated factor pattern matrix is only an intermediate solution. It defines a common factor space that contains the maximum common variance for any m common factors for these variables. It is not used for factor interpretation.

Step 5: Rotation of Factors

Mathematically, the factor pattern matrix is not unique. Given the model equation $\mathbf{Y} = \mathbf{\Lambda X} + \mathbf{E}$, we can find alternative factor pattern matrices and common factors by linear transformations of them. Let $\mathbf{T}$ be an $m \times m$ transformation matrix of full rank and $\mathbf{T}^{-1}$ its matrix inverse. Then $\mathbf{Y} = \mathbf{\Lambda T T}^{-1}\mathbf{X} + \mathbf{E} = \mathbf{\Lambda}^*\mathbf{X}^* + \mathbf{E}$, with $\mathbf{\Lambda}^* = \mathbf{\Lambda T}$ and $\mathbf{X}^* = \mathbf{T}^{-1}\mathbf{X}$. This also has the form of a factor analysis equation. So, which factor pattern matrix should be our solution? L. L. Thurstone (1947) solved this problem with the idea of simple structure. He argued that if most of the observed variables were not functions of all of the common factors of their domain, then the vectors representing them in common factor space would fall in "coordinate hyperplanes" or subspaces of the full common factor space. Each hyperplane or subspace would be spanned by, at most, $m - 1$ of the common factors, and all variables within those subspaces would be functions of just the common factors spanning the hyperplane. The common factors of the full common factor space then would be found at the intersections of these "coordinate hyperplanes," because they would be among the basis vectors of each of $m - 1$ hyperplanes. If the coordinate hyperplanes could be identified by discovering subsets of the variables occupying these subspaces of lower dimension, then the common factors would be identified at their intersections. Furthermore, different selections of variables from the domain would still identify the same common factors at the intersections of the hyperplanes. Hence, the solution for the factors is not unique to the selection of variables from the domain and is an objective, invariant result over almost all selections of observed variables from the domain. To discover these hyperplanes, Thurstone proposed using hypothetical vectors called *reference axes* inserted into the common factor space. A subspace of the common factor space would be a subspace of vectors orthogonal to a reference axis and would be like a parasol whose ribs represent vectors in the subspace, with the reference axis its handle. Thus, one would move each reference axis around in the common factor space seeking different sets of variables to fall in the "parasol" orthogonal to the reference axis. These subsets of variables would define the coordinate hyperplanes. Originally, Thurstone used graphical, two-dimensional plots for each pair of factors and moved his reference axes manually in these two-dimensional spaces to discover sets of variables that would line up orthogonal to the reference axes. This was slow work. Later, with the advent of computers, analytic criteria for simple structure were formulated and the process of finding simple structure solutions automated. It is important, however, to realize that simple structure does not imply uncorrelated or orthogonal factors. The common factors may be correlated. Thus, one should avoid rotational procedures such as VARIMAX, which forces the common factors to be mutually orthogonal, if one wants a genuine simple structure solution. Good algorithms for simple structure that are generally available are direct Oblimin and Promax. Other algorithms claim a modest superiority over these, but they are not generally available in commercial factor analysis programs.

In our example, we rotated our four-factor solution to simple structure using direct Oblimin rotation. The program produced a factor pattern matrix, a factor structure matrix, and a matrix of correlations among the factors. The factor pattern matrix contains weights like regression weights for deriving the observed variables from the common factors. The matrix is the most useful in interpretation of the factors, because these weights will be invariant under restriction of range across selected subpopulations of subjects. Furthermore, the pattern weights clearly show which variables are and are not functions of which common factors. The factor structure matrix contains the correlations between the observed variables and the common factors. It is itself the matrix product $\mathbf{\Lambda\Phi}$ of the factor pattern and factor correlation matrices. So, once these two are obtained, the factor structure matrix is redundant. Furthermore, the factor structure matrix and the matrix of correlations among factors are not invariant under restriction of range or selection of subjects.

Step 6: Factor Interpretation

The method of factor interpretation is eliminative induction. One looks down each column of the factor pattern matrix for those variables having large "loadings" on the factor. One interprets the factor as that hypothetical variable that is common to those variables with large loadings but absent in variables with near-zero loadings. In Table 3, we find something like positive orientation to others or "kindness" to be what is common to those variables having high loadings on the first factor. Ability seems to be the common element for the second factor, whereas extraversion is the common element for the third. The fourth factor indeed is something common to just helpful and cooperative, and these variables also have modest loadings as expected on kindness and ability. The correlations among factors in Table 4 suggest that kindness and extraversion share something in common and less with ability. In some cases, factor analysts will factor analyze the correlations among the factors to obtain second-order common and unique factors.

—Stanley A. Mulaik

Table 3 Factor Pattern Loadings

	1	2	3	4
FRIEND	.78317	.04561	.06936	.02296
SYMPATH	.84525	-.05340	-.01319	.12206
KIND	1.03068	.02353	-.09171	-.04496
AFFECTN	.79470	-.03680	.14617	.03676
INTELL	-.07708	.88650	-.01461	.03989
CAPABL	.02454	.92586	.01284	-.02959
CMPTNT	-.07117	.90317	.00333	.10189
SMART	.10794	.91176	.00614	-.09064
TALKTV	.01144	.03235	.84101	-.09020
OUTGO	-.04548	-.00038	.92307	.08421
GREG	.01553	-.01468	.88010	.01090
EXTRAV	-.02696	-.01428	.93815	-.03029
HELPFL	.32864	.11450	.12744	.44996
COOPER	.23477	.10052	.11966	.56880
SOCIAB	.07860	.00542	.82472	.11774

Table 4 Correlation Between Common Factors

	1	2	3	4
FACTOR 1	1.00000			
FACTOR 2	.21857	1.00000		
FACTOR 3	.52371	.28226	1.00000	
FACTOR 4	.72944	.33731	.52443	1.00000

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FACTORIAL DESIGN

A factorial design involves the simultaneous study of two or more variables or factors on some other variable or variables. The factors may be manipulated or measured. Each factor consists of two or more levels or categories. The levels may differ qualitatively or quantitatively. For example, the qualitative factor of marital status may consist of the five levels of never married, married, separated, divorced, and widowed. Quantitative factors may comprise particular values (such as increasing dosages of a drug) or a range of values (such as the four age groups of 20–29, 30–39, 40–49 and 50–59).

A factorial design may be further described in terms of the number of factors, the number of factors and levels within each factor, whether cases have been randomized to factors or treatments, and whether cases are measured on more than one occasion. Factors may be referred to as "ways," so that a two-factor design may be called a two-way design, a three-factor design a three-way design, and so on. Alternatively, the design may be described in terms of the number of levels within each factor. A design that consists of three factors, two having two levels and the third having four levels, may be designated a $2 \times 2 \times 4$ ("a two by two by four") factorial design. A completely randomized factorial design is where each case has been RANDOMLY ASSIGNED to one and only one combination of factor levels or cells. A mixed factorial design comprises at least one factor where cases are measured on more than one occasion and one factor where cases are measured on only one occasion.

Ronald Fisher (1935) suggested that the factorial design had three advantages over the single-factor design. The first advantage is that it is more efficient or economical in that it requires fewer cases or observations for the same degree of precision or power. Compared with a single-factor design, a two-factor or two-way factorial design requires half as many cases, a three-way design a third as many cases, a four-way design a quarter as many cases, and so on (Snedecor, 1937). The reason for this is that the values of one factor are averaged across the values of the other factors. The second advantage is that it is more comprehensive in that it allows the interaction between two or more factors to be examined. The third advantage is that it enables greater GENERALIZABILITY of the results in that a factor has been investigated over a wider range of conditions. A fourth advantage is that it may provide a more sensitive or powerful test of a factor if that factor does not interact substantially with one or more factors in that the other factors may account for some of the unexplained or error variance (Stevens, 2001).

—Duncan Cramer

See also EXPERIMENT

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FACTORIAL SURVEY METHOD (ROSSI'S METHOD)

Humans form ideas about the way the world works. They also form ideas about the way the world ought to work. These positive and normative ideas can be represented by equations, termed, respectively, *positive-belief equations* and *normative-judgment equations.* Rossi's factorial survey method makes it possible to estimate these equations-inside-the-head.

The positive-belief and normative-judgment equations are linked to two further equations—an equation describing the determinants of components of the beliefs or judgments, called a *determinants equation,* and an equation describing consequences of the belief/judgment components, called a *consequences equation.*

For example, individuals form ideas about earnings determination and, concomitantly, about the earnings they regard as just for themselves and others. Both the ideas about actual earnings determination and about just earnings determination are themselves the product of personal and social factors, such as information about the occupational structure and