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Making Sense of Factor Analysis

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An Overview of Factor Analysis

Not all science is hypothesis testing. Sometimes we are interested in the structure of a particular phenomenon. Factor analysis provides us with the means to undertake a structural analysis of that problem. In the Introduction, for example, we identified a construct we wished to explore in greater depth: the concerns of individuals who are considering undergoing genetic testing for cancer. Our interim goal is to develop an instrument of data collection that would adequately measure and reflect the structure of this construct. Ultimately, we would like to formulate programs of intervention that would address the specific concerns of individuals who make up this population.

A review of the literature indicates that there may be several different but possibly interrelated subdimensions of concerns about genetic testing contained within this single construct. Through our knowledge of the theoretical literature as well as discussions with health care providers and persons considering undergoing genetic testing, we have identified a large set of items or statements, which may-or may not-reflect the dimensions of concerns related to genetic testing. We intend to present these statements to a large group of potential recipients of genetic testing, to receive their feedback about the importance of these concerns to them, and to simplify the instrument into a user-friendly, easy-to-complete form that could be used in future research.

Although these tasks appear, on the surface, to be easily accomplished, there are a number of questions related to instrument development that need to be answered prior to undertaking the study. For example, how will we select these items? Do those selected items cover the subject completely? How many items should there be? To how many subjects should we administer this instrument?

Once we have determined the sample size and number and content of the items, we will need to identify the most appropriate statistical analyses that should be used with the collected data. A review of the measurement literature suggests that *factor analysis* might be a useful tool to analyze the structure of this construct, called Concerns About Genetic Testing. How can we use factor analysis, and what are the processes underlying this procedure? How is factor analysis different from other statistical procedures (e.g., the *t* test, analysis of variance [ANOVA], and multiple regression)? A number of statistical computer packages offer fast, economical factor analysis programs. What are the differences and similarities between these programs? How do we decide on the best program to use and, once we have done that, how would we interpret the results reported in the computer printouts?

We realize that these may be daunting questions to which you would like immediate answers. Why are sample

size and number of items important to us? What is meant by the “structure” of a construct, and what is its relevance to factor analysis? In these next chapters, we hope to provide you with answers to these puzzling questions.

CHARACTERISTICS OF FACTOR ANALYSIS

Factor analysis is not a single statistical method. Unlike the t test or ANOVA, it is not a test of differences between groups of subjects. Rather, factor analysis represents a complex array of structure-analyzing procedures used to identify the interrelationships among a large set of observed variables and then, through data reduction, to group a smaller set of these variables into dimensions or *factors* that have common characteristics (Nunnally & Bernstein, 1994).

What is a factor? Most simply summarized, a factor is a linear combination or cluster of related observed variables that represents a specific underlying dimension of a construct, which is as distinct as possible from the other factors included in the solution (Tabachnick & Fidell, 2001). As you will read in Chapter 8, Leske (1991) used the techniques of factor analysis to identify five underlying dimensions or factors related to the Critical Care Family Needs Inventory (CCFNI), an instrument designed to assess the needs of family members of the critically ill. She labeled these distinct CCFNI factors as *needs for support, comfort, information, proximity, and assurance*.

In the genetic testing example, the methods of factor analysis will help us examine the interrelationships among the items or statements that we believe are measuring this construct called Concerns About Genetic Testing, and then to identify its subdimensions. Our ultimate goal in using the methods of factor analysis is to arrive at a parsimonious or reduced set of factors that summarizes and describes the structural interrelationships among the items in a concise and understandable manner (Gorsuch, 1983).

Factor analysis can be used for theory and instrument development and assessing construct validity of an established instrument when administered to a specific population. Once the internal structure of a construct has been established, factor analysis may also be used to identify external variables (e.g., gender and social status position) that appear to relate to the various dimensions of the construct of interest (Nunnally & Bernstein, 1994).

EXPLORATORY VERSUS CONFIRMATORY FACTOR ANALYSIS

There are two basic types of factor analysis: exploratory and confirmatory. *Exploratory factor analysis* (EFA) is used when the researcher does not know how many factors are necessary to explain the interrelationships among a set of characteristics, indicators, or items (Gorsuch, 1983; Pedhazur & Schmelkin, 1991; Tabachnick & Fidell, 2001). Therefore, the researcher uses the techniques of factor analysis to explore the underlying dimensions of the construct of interest. This was the approach that Leske (1991) used in her conceptualization of the dimensions of needs of families of the critically ill. EFA is the most commonly used form of factor analysis in health care research. It is what we will use to examine the dimensions of Concerns About Genetic Testing.

In contrast, *confirmatory factor analysis* (CFA) is used to assess the extent to which the hypothesized organization of a set of identified factors fits the data (Nunnally & Bernstein, 1994; Pedhazur & Schmelkin, 1991). It is used when the researcher has some knowledge about the underlying structure of the construct under investigation. CFA could also be used to test the utility of the underlying dimensions of a construct identified through EFA, to compare factor structures across studies, and to test hypotheses concerning the linear structural relationships among a set of factors associated with a specific theory or model. Pett, Wampold, Turner, and Vaughan-Cole (1999), for example, used CFA to test a hypothesized model predicting the paths of influence of divorce on young children's psychosocial adjustment.

When undertaking a factor analysis using EFA, it is common practice to use more traditional statistical computer packages (e.g., SPSS, SAS, and BMDP) for the statistical analyses. CFA, on the other hand, requires a comprehensive analysis of covariance structures (Byrne, 1989). This form of measurement model is available in *structural equation modeling* (SEM). LISREL (Joreskog & Sörbom, 1989) and EQS (Bentler, 1985) are two statistical computer packages that are used to undertake SEM analyses.

ASSUMPTIONS OF EXPLORATORY FACTOR ANALYSIS

Because the focus of this book is on beginning instrument development in health care research, we will concentrate on exploratory factor analysis. Before we begin that exploration, there are some assumptions about EFA that need to be considered.

A basic assumption of EFA is that within a collection of observed variables, there exists a set of underlying factors, smaller in number than the observed variables, that can explain the interrelationships among those variables (Kim & Mueller, 1978). Because the initial steps of factor analysis are performed using Pearson product moment correlations, many of the assumptions relevant to this parametric statistic are applicable to factor analysis (e.g., large sample sizes, continuous distributions, and linear relationships among items).

Some of the assumptions related to the Pearson product moment correlation, however, are violated in factor analysis. As you will see in Chapter 2, the response categories for each individual scale item are most often constructed using dichotomous *yes, no* responses or are based on ordinal-level Likert scales. Tabachnick and Fidell (2001) also argue that normality of distributions is not critical if the researcher's intent is to explore, summarize, and describe relationships among variables. If, on the other hand, the goal is to identify the number of factors that underlie the items being examined, then multivariate normality is an issue about which to be concerned. *Multivariate normality* implies that all of the variables being considered and the linear combinations of those variables are normally distributed. Hair, Anderson, Tatham, and Black (1995), Pett (1997), and Tabachnick and Fidell (2001) offer extensive discussion and advice concerning approaches to screening data for both univariate and multivariate normality. As these issues arise throughout the chapters, we will discuss various approaches to evaluating these assumptions.

HISTORICAL DEVELOPMENTS OF FACTOR ANALYSIS

Factor analysis owes its earliest development to several groups of British and American psychologists whose work from 1900 to the late 1930s focused on addressing problems related to the structural modeling of such constructs as the dimensions of human intelligence (e.g., Garnett, 1919; Pearson, 1901; Spearman, 1904, 1923, 1927, 1929; Thurstone, 1935, 1937a, 1937b; Wilson, 1928). Unfortunately, the wide expanse of the Atlantic Ocean not only separated two continents, it also divided these psychologists into two separate camps that, at times, either ignored or vociferously challenged the other's contributions (Harman, 1976; Mulaik, 1986).

In Britain, Spearman and his colleagues (e.g., Burt, 1939, 1941; Garnett, 1919; Ledermann, 1937, 1938; Spearman, 1904, 1922, 1923, 1927, 1928, 1929, 1930a, 1930b; Thomson, 1934, 1936, 1938) pursued the concept of the two-factor *g* theory of human intelligence. Briefly, supporters of this two-factor theory of intelligence initially argued that all inter-correlations among tests of mental ability could be explained by two fac-

tors: (1) a single general factor, or *g* factor, that represented *general intelligence* and (2) a unique factor that was associated with a particular test. Because these unique factors are uncorrelated with one another, the *g* factor accounted for all the correlation among tests of mental abilities (Nunnally & Bernstein, 1994). Although this two-factor theory was later modified to include group factors as well (Garnett, 1919; Spearman, 1927), much of the development of early factor analysis could be attributed to the search for the existence of a single general factor of intelligence (Burt, 1966; Harman, 1976).

In the United States, the group of Thurstone and his students (a.k.a., the Thurstonians) challenged the adequacy of Spearman's two-factor theory to describe tests of mental abilities. Like Garnett (1919), they developed the concept of multiple-factor analysis and applied these methods to a variety of psychometric problems (Thurstone, 1931, 1940, 1947, 1948, 1954). Mulaik (1986) notes that although the British psychologists made significant contributions to the early development of factor analysis, once the Thurstonians arrived on the scene in the early 1930s, the United States became a major center for the development of factor analysis procedures. This dominance continued until the late 1960s and 1970s, when a number of prominent European psychometricians (e.g., Jöreskog and Sörbom from Scandinavia) made major contributions to the field (Joreskog, 1967, 1969, 1970; Joreskog & Goldberger, 1972; Sörbom, 1974).

A search of the psychology literature via PsycINFO for the use of factor analysis as a statistical technique during the 100-year period 1901-2000 indicated that many of the earliest references to the procedure were organized around discussions and critiques of the theory and mathematics of Spearman's two-factor *g* theory of intelligence (e.g., Dodd, 1929; Meili, 1930; Miner, 1912, 1920; Spearman, 1922, 1923, 1927, 1928, 1929, 1930a, 1930b; Spearman & Holzinger, 1924; Wilson, 1928).

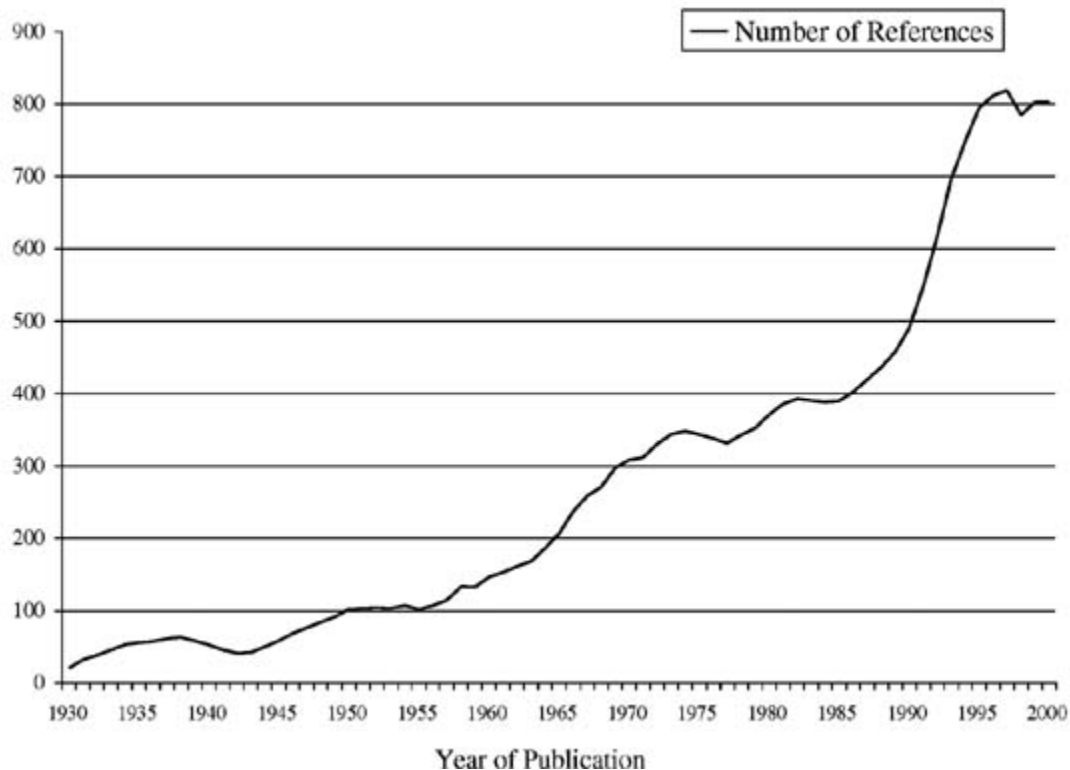
Other highlights of early factor analysis history include Thurstone's (1931) first textbook on test theory and, in 1936, the first issue of the journal *Psychometrika*, which was published by the Thurstone group to provide a forum for their research and theoretical interests (Mulaik, 1986).

Since the 1930s, the use of factor analysis in psychology research has rapidly expanded. It should be noted that although factor analysis has had its fair share of fervent supporters, it has also been met with concerned challengers (Steiger, 1996). Figure 1.1 outlines the geometric growth in the use and examination of factor analysis as a research tool as reported in PsycINFO between 1930 and 2000.

Prior to the 1950s, the use of factor analysis was relatively stable, with fewer than 100 publications on the subject being reported in PsycINFO annually. Since the 1950s, there has been a rapid acceleration in the use

of factor analysis. Several possible reasons for this phenomenon that are related to psychometrics have been suggested (Gulliksen, 1974; Mulaik, 1986) and include

Figure 1.1 References to Factor Analysis in PsycINFO, 1930 to 2000



- the use of factor analysis by Thurstone and his colleagues during World War II to develop selection and criterion variables for use by the military;
- the development in the 1950s of electronic digital computers, which rapidly became readily accessible tools on university campuses;
- the generating of algorithms to compute eigenvalues and eigenvectors, two related elements that are critical to statistical analyses of matrices; and
- the development in the early 1960s of the Varimax rotation, an important time-saving solution to rotations for uncorrelated factors, followed by the development of the Oblimax and Oblimin rotations for correlated factors.

The important contribution of computers to the rapid rise in the use of factor analysis cannot be overstated. Without computers, factor analysis involved extremely labor-intensive computations. During the 1940s and 1950s, for example, the mere undertaking of a factor analysis was often enough to serve as a Ph.D. disser-

tation (Steiger, 1996). Gulliksen (1974), an outstanding theoretician who worked at the Educational Testing Service at Princeton, illustrates the dimensions of this problem with the following comments:

I was a research assistant for a year working on Thurstone's first study of primary mental abilities. The computational work in resolving a battery of about 50 tests into seven primary mental abilities meant that I was supervising a group of about 20 computer clerical workers for about a year. I recall Thurstone lamenting that his Ph.D. candidates would not be able to do factor analysis dissertations because it would not be practical to employ such a crew for each Ph.D. thesis. (p. 251)

The arrival of mainframe computers on university campuses during the 1970s enabled researchers to undertake factor analyses more rapidly and efficiently. Still, given the slowness and restricted use of mainframe computers, such analyses continued to be labor intensive, time-consuming, and expensive by today's standards. It was not until the 1980s, with the advent of personal computers, that factor analysis became a readily available and popular research tool.

For example, Gulliksen (1974) observed that in early 1970, a research worker from the Civil Service came to him for help in analyzing a set of attitude scales:

He came up one afternoon, with his data on punched cards, and we started about 4:00 p.m. to run the preliminary error-detecting program, and we corrected the cards whenever errors were found. In all, including the scaling, correlations, factor analyses, and rotations, although the job was somewhat larger than the primary mental abilities one, we were finished about 3:00 a.m. the next morning. (p. 251)

Today, assuming no errors in the data, the same job would probably take only a few seconds!

USES OF FACTOR ANALYSIS IN HEALTH CARE RESEARCH

A review of other health care disciplines during the past 15 years indicates similar dramatic increases in the use of both exploratory and confirmatory factor analyses. A review of the published articles in PsycINFO indicated more than twice as many published studies reported having used factor analysis in 2000 ($n = 800$) compared with 1985 ($n = 319$).

The rise has been even more dramatic in those health care disciplines that do not have the rich psychometric

history that psychology and education enjoy. For example, for this same 15-year period, the number of research articles reporting the use of factor analysis in the nursing and allied health literature (CINAHL) increased by more than 16,000%, from 2 in 1985 to 326 in 2000. Notable increases in the reported use of factor analysis were also noted in the medical literature (MEDLINE: $n = 97$ in 1985 to $n = 365$ in 2000, 276%; HEALTHSTAR: $n = 74$ in 1985 to $n = 377$ in 2000, 409%). Although the reported uses of factor analysis in the research literature search bases SPORT Discus and AGELINE have remained relatively low ($n = 111$ and $n = 28$, respectively, during 2000), these numbers still represent increases of 311% and 180% for each search base from 1988 figures ($n = 27$ for SPORT Discus and $n = 10$ for AGELINE).¹

What has contributed to this continued increase in the use of factor analysis in the health sciences in particular? Several possibilities come to mind:

- Increased researcher interest in the complex organizational structure of various health-related constructs
- Recent developments in the use of confirmatory factor analysis and structural equation modeling
- Greater sophistication concerning statistics on the part of some health care researchers from all disciplines and levels of expertise
- Increased availability of inexpensive but powerful personal computers, which can undertake analyses quickly and inexpensively
- Availability of increasingly user-friendly statistical computer packages

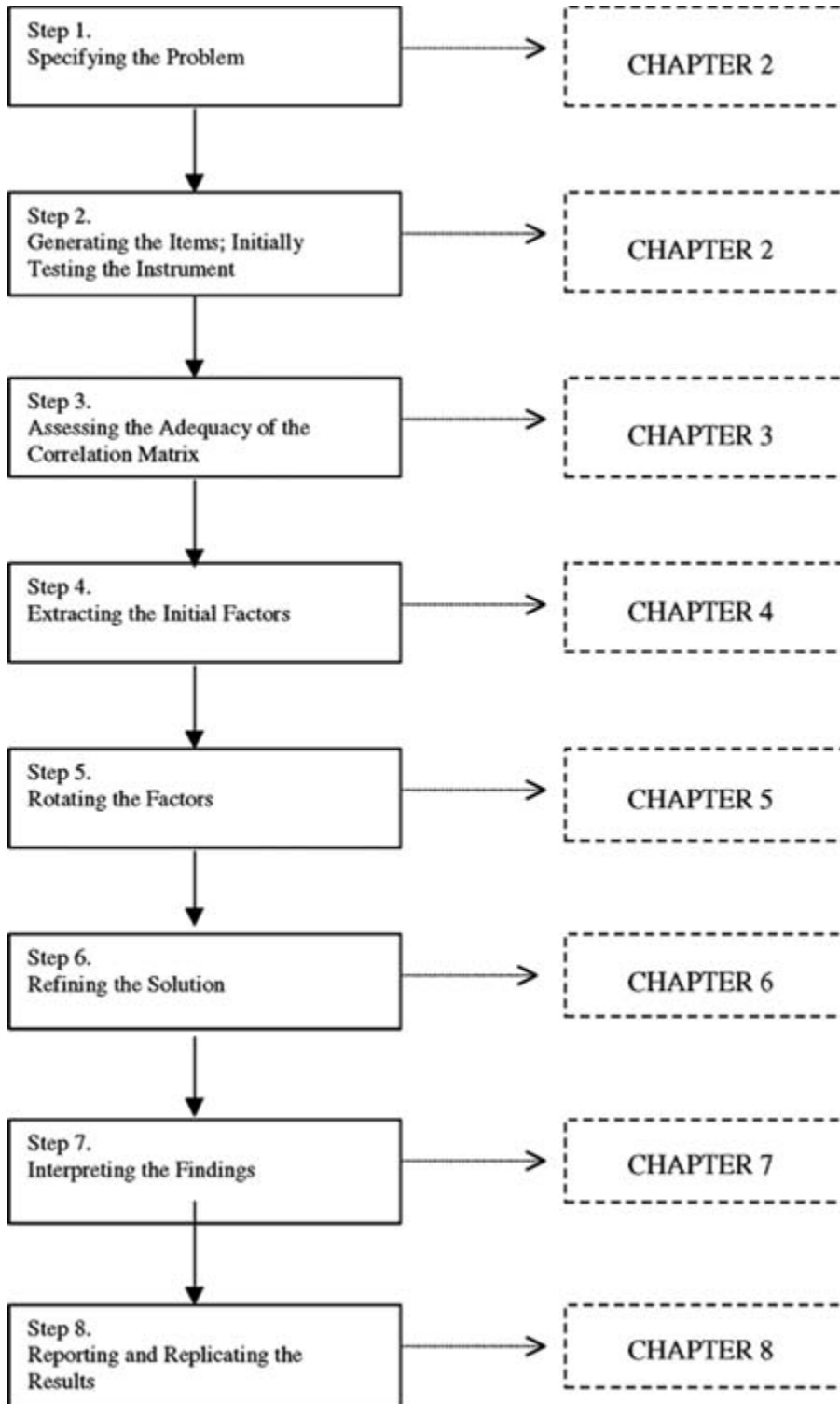
Unfortunately, enhanced user understanding and expertise with regard to measurement theory and factor analysis have not always accompanied the increased use of this statistical method in health care research. Our experience indicates that with the exception of psychology and education, few graduate programs in the health sciences provide their students with strong backgrounds in either of these areas. As Kline (1994) has lamented, "With the advent of powerful computers and the dreaded statistical packages which go with them, factor analysis and other multivariate methods are available to those who have never been trained to understand them" (p. 1).

As a result, we are seeing improper use and reporting of analyses that have been generated from this technique. It is our hope that this text will help to resolve this unfortunate situation by providing you with a clearer understanding of the logic and techniques involved in using factor analysis as a statistical tool for research in the health sciences.

DECISION-MAKING PROCESS IN EXPLORATORY FACTOR ANALYSIS

Regardless of statistical package or level of expertise of the researcher, there are eight basic steps to exploratory factor analysis (Figure 1.2). These steps include specifying the problem, generating the items, assessing the adequacy of the correlation matrix, extracting the initial factors, rotating those factors, refining the solution, interpreting the findings, and, finally, reporting and replicating the results. These are the steps that we will examine in considerable detail in Chapters 2 through 8.

Figure 1.2 A Block Diagram of the Decision-Making Process in Exploratory Factor Analysis



NOTE

1.

The year 1988 is reported here because it is the initial year of reporting for SPORT Discus.

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