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ABSTRACT

First- and higher-order factor analyses are explained from a conceptual rather than a mathematical perspective. A case is made for performing higher-order factor analysis when factors are theoretically related. Actual scores of 301 children on 24 ability measures are used to demonstrate interpretation of second-order factors using the FORTRAN program SECONDOR. Higher-order factor analysis using interpretation aids such as the Schmid-Leiman (1957) solution allows the researcher to examine a complex world in a parsimonious manner. Seven tables illustrate the discussion. (Contains 11 references.) (Author/SLD)

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Hierarchical Analytic Methods that Yield Different Perspectives on Dynamics: Aids to Interpretation

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Abstract

The purpose of the present paper is to explain first- and higher-order factor analyses from a conceptual rather than a mathematical perspective. A case is made for performing higher-order factor analysis when factors are theoretically related. Actual scores of 301 children on 24 ability measures are used to demonstrate interpretation of second-order factors using the FORTRAN program SECONDOR.

Hierarchical Analytic Methods that Yield Different Perspectives on Dynamics: Aids to Interpretation

Most researchers strive to interpret and describe variables in a clear, parsimonious manner. Kerlinger (1984) writes,

> Factor analysis is essentially a method driven by the needs of parsimony; it reduces multiplicities of tests or measures to greater simplicities. It tells us, in effect, what tests or measures belong together: which ones measure the same thing and how much they do so. (p. 245)

Imagine a researcher faced with scores of 301 children on 24 ability tests. As demonstrated later in this paper, factor analysis can be used to reduce 24 variables into a smaller set of first-order factors, thus making interpretation more manageable.

While many researchers are familiar with extracting first-order factors from a matrix of associations (e.g., variance-covariance or correlation matrix), few are familiar with the concept of performing a factor analysis on correlated first-order factors (Kerlinger, 1984). These "factors" of first-order factors are termed second- or higher-order factors. Higher-order factors provide a broader perspective than first-order factors in describing relationships between the original variables (Gorsuch, 1983).

The purpose of the present paper is to explain first- and higher-order factor analyses from a conceptual rather than a mathematical perspective. A case is made for performing higher-order factor analysis when factors are theoretically related. As mentioned previously, actual scores of 301 children on 24 ability measures are used to demonstrate interpretation of second-order factors using the FORTRAN program SECONDOR (Thompson, 1990).

First-Order Factor Analysis

Like many statistical analyses, factor analysis is used to explain shared variance between variables. Simplistically, how much of the relationship (i.e., variance-covariance, correlation) between variables 1 and 2 can be explained by Factor I? Suppose variable 1 is Reading Speed and variable 2 is Reading Comprehension. The correlation between variables 1 and 2 is .90; in other words, variable 1 shares 81% of its variance with variable 2 and vice-versa. This shared variance could be explained by a hypothetical construct or factor called Reading Ability. In essence, factor analysis provides the researcher with a statistical basis for explaining shared variance and defining theoretical constructs.

First-order factor analysis is the first step towards simplifying a set of variables (or other factorable entities) into a smaller set of factors. The relationship between variables is represented in an association matrix such as a variance-covariance or correlation matrix; in factor analysis, matrices represent relationships between variables, factors, or variables and factors. Factor analytic procedures attempt to explain the maximum amount of variance with the fewest number of factors. From the example in the previous paragraph, Reading Ability (Factor I) accounted for 81% of the shared variance between variables 1 and 2. The communality (symbolized $\underline{h}^2$) is a proportion (ranging from 0 to 1) of the original variables' variance explained by the factor.

Various factor analytic procedures analyze different portions of variance when extracting or removing factors; extraction refers to removing shared variance from the matrix of associations in the form of a factor. Describing different sources of variance in factor analysis, Weiss (1971) writes,

> The general factor-analysis model assumes that the total variance of a variable is composed of three components: common variance, unique variance, and error variance. For each variable included in the factor analysis of a correlation matrix, the mix of these three components may be different, but the sum of the components is the same--1.0. (p. 85)

Common variance is the reliable portion of variance (i.e., degree of correlation) which a variable shares with other variables. Unique variance is variance specific to a particular variable. Error variance is unreliable variance which is unexplained and sometimes sample-specific (Weiss, 1971).

Principal components analysis, an extraction procedure, utilizes total variance when extracting factors. Other extraction procedures (e.g., principal factors analysis) utilize common variance. For further discussions on the type of variance used in factor extraction procedures, see Tinsley and Tinsley (1987) and Weiss (1971).

After defining the variance to be analyzed (i.e, total, common) the researcher is faced with the question of how many factors to extract. Like all methodological decisions, choosing the number of factors requires judgment on the part of the researcher. In some instances, the investigator may have theoretical grounds for specifying a number of factors. In most cases, a trade-off exists between the fewest number of factors and the greatest amount of variance explained. Tests of statistical significance, measures of explained variance, and visual representations of factors and explained variance can be used to inform the researcher making these judgments (Tinsley & Tinsley, 1987; Weiss, 1971).

Eigenvalues are often used in making decisions about the number of factors extracted. Much like communalities, eigenvalues are an index of explained variance. However, eigenvalues are not percentages. Rather, the value of an eigenvalue may be between 0 and the number of factored entities (e.g., variables). Typically, factors with eigenvalues greater than 1 are extracted (Guttman, 1954).

After variance and factor decisions are made, the factor analyst must interpret the factors. Factor rotation offers the opportunity to redistribute explained variance in such a way that the factors are more meaningful. Rotation procedures do not explain new variance, rather they redistribute previously explained variance. Factors can be either correlated or uncorrelated with each other following rotation, depending upon the rotation procedure utilized (Gorsuch, 1983).

Orthogonal rotation procedures such as varimax are used when the researcher believes the factors are uncorrelated. Often, the researcher values "simple" structure with each variable correlating on as few factors as possible. Oblique rotation procedures such as promax are used when the researcher believes the factors are related or correlated. Factor analysts with more complex views of reality may value a procedure that allows non-zero relationships between factors (Gorsuch, 1983).

Because oblique solutions offer a more complex view of factors (i.e., first-order factors that are correlated), a higher level of analysis is necessary for interpretation. Gorsuch (1983) writes,

> Rotating obliquely in factor analysis implies that the factors do overlap and that there are, therefore, broader areas of generalizability than just a primary factor. Implicit in all oblique rotations are higher-order factors. It is recommended that these be extracted and examined so that the investigator may gain the fullest possible understanding of the data. (p. 255)

After rotating factors, the researcher must interpret the contributions of variables and factors. Pattern and structure coefficients are useful in making these interpretations. Pattern coefficients are weights used to create scores on the latent factors, just as beta weights are used to calculate scores on the latent variable, YHAT, in regression. Structure coefficients are an index of the relationship of the variables to the factors. Because pattern (factors to variables) and structure (variables to factors) coefficients assume different vantage points, it is recommended that both be interpreted (Gorsuch, 1983).

Higher-Order Factor Analysis

In comparing first- and second-order factor analyses, Thompson (1990) offers the following analogy,

> The first-order analysis is a close-up view that focuses on the details of the valleys and the peaks in mountains. The second-order analysis is like looking at the mountains at a greater distance, and yields a potentially different perspective on the mountains as constituents of a range. (p. 579)

Taking this analogy further, mountains represent the original variables (or other factorable entities) that are analyzed. A first-order analysis could be described as binoculars with a zoom lens. A second-order analysis could be described as binoculars with a wide range lens. Notice that both binoculars (first- and second-order analyses) are focused on the mountains (original variables).

Because second-order factor analysis is a factor analysis of correlated first-order factors, many researchers make the mistake of interpreting second-order factors on the basis of first-order factors (Thompson, 1990). The factor analyst interpreting second-order factors on the basis of first-order factors is interpreting shadows of the shadows of mountains rather than the mountains themselves. To remedy this high level of abstraction, Gorsuch (1983) suggests,

> To avoid basing interpretations upon interpretations of interpretations, the relationships of the original variables to each level of the higher-order factors are determined....Interpreting from the variables should improve the theoretical understanding of the data and produce a better identification of each higher-order factor. (pp. 245-246).

To examine the original variables from the higher-order perspective, Gorsuch (1983) recommends multiplying the first-order pattern matrix by the second-order pattern matrix. The resulting product matrix (first-order x second-order) can then be rotated orthogonally by the varimax procedure (Thompson, 1990). The resulting matrix allows the researcher to interpret the higher-order factors' relationships to the original variables.

Another method for interpreting the second-order factors on their relationship to the original variables is to apply the Schmid-Leiman (1957) solution. In this solution, the first-order factors are made orthogonal to the second-order factors. Variance explained by second-order factors is extracted first. The first-order factors are then residualized of all variance present in the second-order factors (i.e., first-order factors are residualized using the second-order factors). According to Schmid and Leiman (1957), this solution "...not only preserves the desired interpretation characteristics of the oblique solution, but also discloses the hierarchical structuring of the variables" (p .53). Borrowing again from Thompson's (1990) analogy, this solution allows the researcher to directly view the mountains from a second-order perspective.

An Example Using SECONDOR

This section gives an example of second-order factor analysis using the FORTRAN program, SECONDOR (Thompson, 1990) with 24 ability measures from 301 junior high children (Holzinger & Swineford, 1939). SECONDOR performs both first-order and second-order factor analyses using either original data or a correlation matrix. The reader interested in SECONDOR is referred to Thompson (1990). The Holzinger and Swineford (1939) data provide an excellent example of one second-order or "G" factor. Table 1 lists the 24 ability tests or variables used in the factor analysis.

SECONDOR executes a first-order factor analysis giving unrotated, orthogonal, and oblique solutions. Four factors were extracted (eigenvalues > 1) using principal components analysis. The factors were rotated obliquely using the promax-rotation procedure. Table 2 presents the first-order pattern coefficients. Table 3 presents the first-order structure coefficients.

Inspection of both pattern and structure coefficients aided in the interpretation of first-order factors. Factor I could be called Verbal Ability with high correlations on General

Information (5), Paragraph Comprehension (6), Sentence Completion (7), and Word Meaning (9). Factor II could be called Numerical Ability with high correlations on Speeded Addition (10) and Speeded Counting of Dots (12). Factor III could be called Visual Ability with high correlations on Visual Perception (1), Cubes (2), and Thorndike Lozenges (4). Factor IV could be called Recognition Ability with high correlations on Memory of Target Words (14), Memory of Target Numbers (15), and Memory for Object-Number Associations (17).

Because the first-order factors interpreted above are based on an oblique solution, the first-order factors are correlated. Table 4 presents the first-order factor correlation matrix. The correlation between first-order factors suggests examining the variables/factors from a second-order perspective (Gorsuch, 1983).

One second-order or "G" factor was extracted (eigenvalue = 2.069). Table 5 presents the second-order pattern matrix (first-order factors x second-order factor) and communalities. Table 6 presents the second-order product matrix and communalities; as mentioned previously, this matrix is a product of the matrices in Tables 2 and 5. The resulting product matrix focuses on the original variables from the second-order viewpoint (Gorsuch, 1983). Because a single second-order factor was extracted, no rotation was possible.

The "G" factor accounts for approximately 30% of the original variance. The variables Paragraph Comprehension (6),

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Word Meaning (9), Speed Coding (11), Math Number Puzzles (21), Completion of Math Series (23), and Mixed Math Fundamentals (24) had large squared structure correlations with this factor.

Table 7 presents the Schmid-Leiman solution and communalities. As mentioned previously, this solution offers a first- and second-order factor structure. The first-order factors are orthogonal to the one second-order factor. Interpretation of the first-order solution is particularly useful for examining variance unexplained by the "G" factor. Inspection of the first-order factors shows high correlations involving General Information (0.598), Paragraph Comprehension (0.564), Sentence Completion (0.632), Word Meaning (0.568), Speeded Addition (-0.638), Speeded Counting of Dots (-0.582), and Memory of Target Words (0.563). Using the Schmid-Leiman (1957) solution, the researcher can determine what the second-order factor does and does not explain in relation to the original variables.

Discussion

In short, higher-order factor analysis offers different perspectives on reality and factor structure. Using this approach, the factor analyst is free to examine varying levels of generalization and specificity. Despite this freedom, some methodologists such as Nunnally (1978) do not encourage the use of second-order factor analysis. Nunnally (1978) writes,

> The average psychologist has difficulty in understanding first-order factors, and this difficulty is increased with

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> higher-order factors....she or he is likely to make some misinterpretations. Also, if factor analysis is partly founded on the principle of parsimony, it is reasonable to question the parsimony of having different orders of factors. (pp. 431-432)

By arguing against different orders of factors, Nunnally (1978) implies that human behavior should be parsimonious and would be best described by first-order factors. This logic appears flawed by what Hume (1957) would call the "is/ought" error. As Strike (1979) explains, "To deduce a proposition with an 'ought' in it from premises containing only 'is' assertions is to get something in the conclusion not contained in the premises, something impossible in a valid deductive argument" (p. 13).

Clearly, human behavior has no obligation to be straightforward as researchers have no obligation to take a simplistic view of the world. Higher-order factor analysis using interpretation aids such as the Schmid-Leiman (1957) solution allows the researcher to examine a complex world in a parsimonious manner.

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Table 1

Listing of Ability Tests from Holzinger and Swineford (1939) Data

No.	ABBREVIATION	Test
1	VISUALPERCEP	Visual Perception
2	SPATIALRELAT	Cubes (spatial task)
3	PAPERFORMBOA	Paper Form Board (spatial task)
4	THORNDIKELOZ	Thorndike Lozenges (spatial task)
5	GENERALINFOR	General Information-Verbal
6	PARACOMPREHE	Paragraph Comprehension
7	SENCOMPLETIO	Sentence Completion
8	WORDCLASSIFI	Word Classification
9	WORDMEANINGT	Word Meaning
10	SPEEDADDITIO	Speeded Addition
11	SPEEDCODETES	Speeded Coding (code shapes with letter)
12	SPEEDCOUNTDO	Speeded Counting of Dots
13	SPEEDDISCRIM	Speeded Discrimination of Curved and Straight Letters
14	MEMORYWORDST	Memory of Target Words
15	MEMORYNUMBER	Memory of Target Numbers
16	MEMORYSHAPES	Memory of Target Shapes
17	MEMOBJNUMASS	Memory of Object-Number Association
18	MEMNUMOBJASS	Memory of Number-Object Association
19	MEMFIGWORDAS	Memory of Figure-Word Association
20	DEDUCTIVEMAT	Deductive Math
21	MATNUMPUZZLE	Math Number Puzzles
22	MATHWORDPROB	Math Word Problems
23	COMPLETEMATH	Completion of Number Series
24	MATHFUNDAMEN	Mixed Math Fundamentals

Note. This table lists the names, numbers, and abbreviations of 24 ability tests given to 301 junior high children. The data were obtained from Holzinger and Swineford (1939).

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Table 2

First-Order Pattern Matrix

Variable		Factors I	II	III	IV
1	VISUALPERCEP	0.078	0.042	0.676	0.009
2	SPATIALRELAT	-0.062	-0.156	0.732	-0.083
3	PAPERFORMBOA	0.001	0.053	0.613	-0.192
4	THORNDIKELOZ	-0.251	0.039	0.792	0.078
5	GENERALINFOR	0.910	0.031	-0.060	-0.131
6	PARACOMPREHE	0.859	-0.026	-0.026	0.021
7	SENCOMPLETIO	0.962	-0.026	-0.089	-0.103
8	WORDCLASSIFI	0.767	-0.005	0.036	0.013
9	WORDMEANINGT	0.864	-0.053	0.045	-0.011
10	SPEEDADDITIO	-0.012	0.869	-0.223	0.024
11	SPEEDCODITES	0.153	0.627	-0.018	0.131
12	SPEEDCOUNTDO	-0.107	0.792	0.149	-0.126
13	SPEEDDISCRIM	-0.086	0.619	0.380	-0.109
14	MEMORYWORDST	0.059	-0.143	-0.089	0.788
15	MEMORYNUMBER	-0.238	-0.127	0.119	0.758
16	MEMORYSHAPES	-0.030	-0.037	0.364	0.517
17	MEMOBJNUMASS	-0.095	0.301	-0.183	0.641
18	MEMNUMOBJASS	-0.036	0.152	0.026	0.541
19	MEMFIGWORDAS	0.204	0.016	0.047	0.418
20	DEDUCTIVEMAT	0.218	-0.165	0.467	0.232
21	MATNUMPUZZLE	0.129	0.320	0.392	0.060
22	MATHWORDPROB	0.450	-0.038	0.348	0.063
23	COMPLETEMATH	0.285	0.065	0.506	0.080
24	MATHFUNDAMEN	0.399	0.304	0.029	0.185

Note. This table presents the first-order, promax-rotated pattern matrix using a four factor solution.

Table 3

First-Order Structure Matrix

Variable		Factors I	II	III	IV
1	VISUALPERCEP	0.405	0.278	0.727	0.282
2	SPATIALRELAT	0.193	0.019	0.627	0.092
3	PAPERFORMBOA	0.235	0.175	0.564	0.038
4	THORNDIKELOZ	0.152	0.225	0.716	0.279
5	GENERALINFOR	0.848	0.273	0.322	0.168
6	PARACOMPREHE	0.845	0.262	0.367	0.294
7	SENCOMPLETIO	0.878	0.235	0.309	0.184
8	WORDCLASSIFI	0.786	0.269	0.391	0.283
9	WORDMEANINGT	0.863	0.247	0.421	0.279
10	SPEEDADDITIO	0.186	0.805	0.046	0.247
11	SPEEDCODETES	0.400	0.719	0.289	0.396
12	SPEEDCOUNTDO	0.185	0.758	0.299	0.166
13	SPEEDDISCRIM	0.259	0.668	0.492	0.208
14	MEMORYWORDST	0.237	0.125	0.164	0.727
15	MEMORYNUMBER	0.031	0.095	0.231	0.674
16	MEMORYSHAPES	0.300	0.246	0.516	0.619
17	MEMOBJNUMASS	0.139	0.437	0.085	0.651
18	MEMNUMOBJASS	0.210	0.337	0.241	0.591
19	MEMFIGWORDAS	0.372	0.245	0.289	0.509
20	DEDUCTIVEMAT	0.456	0.133	0.597	0.409
21	MATNUMPUZZLE	0.437	0.505	0.570	0.351
22	MATHWORDPROB	0.618	0.242	0.564	0.321
23	COMPLETEMATH	0.566	0.344	0.684	0.373
24	MATHFUNDAMEN	0.578	0.512	0.369	0.437

Note. This table presents the first-order, promax-rotated structure matrix using a four factor solution.

Table 4
First-Order Factor Correlation Matrix

	Factors			
	I	II	III	IV
I	1.000	-0.336	-0.459	0.339
II		1.000	0.306	-0.350
III			1.000	-0.343
IV				1.000

Note. This table presents the correlation matrix between the first-order, promax-rotated factors.

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Table 5

Second-Order Pattern Matrix and Communalities

First-Order Factors	G (Second-Order Factor)	h^2
I	0.754	0.568
II	-0.679	0.461
III	-0.742	0.551
IV	0.699	0.489

Note. This table presents the second-order pattern matrix and communalities.

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Table 6

Second-Order Product Matrix and Communalities

Variable	Second-Order Factor	h^2
1 VISUALPERCEP	0.595	0.354
2 SPATIALRELAT	0.333	0.111
3 PAPERFORMBOA	0.358	0.128
4 THORNDIKELOZ	0.480	0.231
5 GENERALINFOR	0.571	0.326
6 PARACOMPREHE	0.625	0.390
7 SENCOMPLETIO	0.570	0.325
8 WORDCLASSIFI	0.610	0.373
9 WORDMEANINGT	0.641	0.411
10 SPEEDADDITIO	0.431	0.186
11 SPEEDCODETES	0.619	0.384
12 SPEEDCOUNTDO	0.480	0.230
13 SPEEDDISCRIM	0.560	0.314
14 MEMORYWORDST	0.432	0.187
15 MEMORYNUMBER	0.353	0.124
16 MEMORYSHAPES	0.584	0.341
17 MEMOBJNUMASS	0.445	0.198
18 MEMNUMOBJASS	0.473	0.224
19 MEMFIGWORDAS	0.491	0.242
20 DEDUCTIVEMAT	0.562	0.316
21 MATNUMPUZZLE	0.648	0.420
22 MATHWORDPROB	0.615	0.379
23 COMPLETEMATH	0.690	0.477
24 MATHFUNDAMEN	0.659	0.434

Note. This table presents the second-order product matrix (first-order pattern x second-order pattern) and communalities. Since a single second-order factor was extracted, no rotation was possible.

Table 7

Schmid-Leiman Solution and Communalities

	Variable	G	First-Order Solution				
			I	II	III	IV	h^2
1	VISUALPERCEP	0.595	0.051	-0.031	**-0.453**	0.006	0.563
2	SPATIALRELAT	0.333	-0.041	0.114	**-0.490**	-0.060	0.369
3	PAPERFORMBOA	0.358	0.001	-0.039	**-0.411**	-0.137	0.318
4	THORNDIKELOZ	0.480	-0.165	-0.029	**-0.531**	0.056	0.543
5	GENERALINFOR	0.571	**0.598**	-0.022	0.040	-0.093	0.694
6	PARACOMPREHE	0.625	**0.564**	0.019	0.017	0.015	0.710
7	SENCOMPLETIO	0.570	**0.632**	0.019	0.060	-0.073	0.734
8	WORDCLASSIFI	0.610	**0.504**	0.004	-0.024	0.009	0.627
9	WORDMEANINGT	0.641	**0.568**	0.039	-0.030	-0.008	0.736
10	SPEEDADDITIO	0.431	-0.008	**-0.638**	0.150	0.017	0.616
11	SPEEDCODETES	0.619	0.100	**-0.461**	0.012	0.094	0.615
12	SPEEDCOUNTDO	0.480	-0.070	**-0.582**	-0.100	-0.090	0.591
13	SPEEDDISCRIM	0.560	-0.057	**-0.454**	-0.254	-0.078	0.594
14	MEMORYWORDST	0.432	0.039	0.105	0.060	**0.563**	0.520
15	MEMORYNUMBER	0.353	-0.156	0.093	-0.079	**0.542**	0.458
16	MEMORYSHAPES	0.584	-0.020	0.027	-0.244	**0.370**	0.539
17	MEMOBJNUMASS	0.445	-0.063	-0.221	0.123	**0.458**	0.476
18	MEMNUMOBJASS	0.473	-0.024	-0.111	-0.017	**0.387**	0.387
19	MEMFIGWORDAS	0.491	0.134	-0.012	-0.031	0.299	0.350
20	DEDUCTIVEMAT	0.562	0.144	0.121	**-0.313**	0.166	0.477
21	MATNUMPUZZLE	0.648	0.085	-0.235	-0.263	0.043	0.553
22	MATHWORDPROB	0.615	0.296	0.028	-0.233	0.045	0.523
23	COMPLETEMATH	0.690	0.187	-0.048	**-0.339**	0.057	0.632
24	MATHFUNDAMEN	0.659	0.262	-0.223	-0.020	0.132	0.570

Note. The G column represents the second-order solution. The first-order solution is based on variance orthogonal to the second-order solution. All first-order values > |.30| indicated in bold.