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ABSTRACT

This paper conceptually explains higher-order factor analysis and methods for interpretation. A review of first-order factor analysis is presented that provides the foundation for the summary of second-order factor analysis. Higher order factors are derived from the correlations between the lower-level factors. An example study is provided to make the discussion concrete and to assist in understanding interpretation of higher-order factor analysis. The heuristic example involves a study of time orientation among students completing a measure of attitudes and beliefs thought related to time perspective. The computer program SECONDOR is used to identify first-order factors and second-order factors. The use of higher-order factor analysis allows researchers to examine data from different levels and perspectives. Two tables and two figures illustrate the discussion. (Contains 14 references.) (Author/SLD)

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The Use of Second-Order Factor Analysis in Psychological Research

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Abstract

The purpose of the present paper is to conceptually explain higher-order factor analysis and methods for interpretation. A review of first-order factor analysis is presented and provides the foundation for the summary of second-order factor analysis. An example study is provided to make the discussion concrete and assist in understanding interpretation of higher-order factor analysis. The heuristic example involves a study of time orientation.

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The Use of Second-Order Factor Analysis in Psychological Research

A primary purpose of scientific inquiry involves examining and summarizing relationships between variables or groups of people under given sets of conditions (Gorsuch, 1983). However, within the social sciences, a field of study may provide vast amounts of information that can be overwhelming and difficult to interpret (Cronbach, 1990). One method developed by psychologists to assist in interpreting large amounts of data is factor analysis (Holzinger, 1941). As Gorsuch (1983) states, "...the aim is to summarize the interrelationships among the variables in a concise but accurate manner as an aid in conceptualization" (p. 2). Tinsley and Tinsley (1987) describe factor analysis as,

> ...an analytic technique that permits the reduction of a large number of interrelated variables to a smaller number of latent or hidden dimensions. The goal of factor analysis is to achieve parsimony by using the smallest number of explanatory concepts to explain the maximum amount of common variance in a correlation matrix. Factors, in essence, are hypothetical constructs or theories that help interpret the consistency in a data set. The value of factor analysis, therefore is that it provides a meaningful organizational scheme that can be use to interpret the multitude of behaviors analyzed with the greatest parsimony of explanatory constructs. (p. 414)

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In addition to organizing data into interpretable composites, factor analysis is also an explanatory tool (Cronbach, 1990). Factor analytic methods are especially useful in the development of theoretical constructs and the exploration of the nature of structures within a field of study (Kline, 1994).

With the advent of powerful computers and availability of statistical packages, factor analysis is used more often and in a variety of different applications (Kline, 1994). However, as Kerlinger (1984) noted, "while ordinary factor analysis is probably well understood, second-order factor analysis, a vitally important part of the analysis, seems not to be widely known or understood" (p. xivv). The purpose of the present paper is to conceptually explain higher-order factor analysis and methods for interpretation. An example study investigating the construct of time perspective is presented as an example of higher-order factor analysis interpretation using program SECONDOR (Thompson, 1990).

Factor Analysis Basics

It is necessary to first understand the terms associated with factor analytic procedures. Factor analysis is applied to matrices of association (i.e., correlation, variance-covariance, cross-product indices). The most commonly used matrix for factor analysis in behavioral sciences is the correlation matrix (Tinsley & Tinsley, 1987). A correlation matrix consists of correlation coefficients which are numeric measurements of the degree of agreement between two or more variables (Kline, 1994).

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A basic assumption of factor analysis is that there are "strands" of intercorrelated variables that have one or more factors in common. These variables can then be represented more simply in terms of factors. Thus, the aim of factor analysis is to explain the greatest amount of variance among factored entities with the least number of factors. Through factor analysis a large amount of information can be simplified into a smaller set of factors. Kerlinger (1984), describes a factor as,

> ...a hypothetical entity, that is assumed to underlie..measures of all kinds...A factor, in other words, is a latent variable...A *latent variable* is an unobserved variable that presumably underlies certain observed measures. (p. 245)

The elements represented on the factors are called structure coefficients, or in slang, factor "loadings". Factor "loadings" represent the correlation of the variables with the factor scores (Kline, 1994). The weights used to create the factor scores are called pattern coefficients, and are analogous to regression beta weights. Both coefficients are used in factor interpretation and will be examined in more detail in a later section of this treatment.

The communality ($\underline{h}^2$) is the proportion of the variable's variance explained by the full set of factors (Tinsley & Tinsley, 1987). Some types of factor analysis require the researcher to estimate the communality prior to factor analysis. The type of communality estimate to be used depends on the type of analysis (i.e., exploratory or confirmatory). For more detail on communality estimates, see Tinsley and Tinsley (1987).

Factor Extraction Methods

The decision on what factor extraction method to use depends on whether the analysis is to be descriptive or inferential, exploratory or confirmatory. In exploratory analysis, the researcher utilizes the results to produce hypotheses for future study. Confirmatory factor analyses are used to test existing hypotheses regarding the nature and structure of factors. In confirmatory factor analysis the researcher must indicate the number and the nature of the factors before the factor extraction procedure is implemented.

Different factor analysis procedures analyze different parts of variable variance. Variance consists of three parts: common variance, unique variance, and error variance (Weiss, 1971). Common variance is common to more than one variable while unique variance is variance that is distinct to a given variable. Two common exploratory methods are principal components and principal factors. In principal components analysis the total variance (including error variance) is utilized when extracting factors, while in principal factors analysis only the common variance is utilized in factor extraction.

Once the decision regarding the type of analysis to perform is made, in exploratory factor analysis the researcher must decide on the number of factors to interpret. There are several methods available to assist in the decision making in exploratory analysis. One method (e.g., Bartlett, 1950) is through the use of statistical significance testing where it can be determined whether meaningful covariation remains after each factor is extracted. Another method is to label a factor a residual factor if it does not have any factor loadings that are 2-2.5 times greater that the standard of error of the factor loadings. Other methods rely on measures of explained variance for the last factor (i.e., the amount of variance explained by the last factor) or the explained variance for the whole factor solution.

One of the more commonly used methods is Kaiser's criterion, which specifies that only factors with eigenvalues of 1.0 or greater prior to rotation should be retained. In principal components analysis an eigenvalue is the sum of the squared factor loadings on each factor (i.e., the sum of the squared column entries). The eigenvalue is the proportion of the variance explained by the factor (Kline, 1994). Another method used in the decision process is Cattell's scree test where the eigenvalues for all the factors are plotted. At the point where the curve becomes horizontal (a scree) it is assumed that the factors are residual factors (Tinsley & Tinsley, 1987) and those factors are not interpreted.

After determining the number of factors, the researcher must decide what rotation procedure to use. In an unrotated factor matrix the first factor will usually account for the majority of the variance and will be highly correlated with almost all the variables and will be difficult to interpret, as will the remaining factors as well. The amount of variance accounted for does not increase or decrease, at all, in factor rotation. The purpose of rotation is to redistribute the explained variance more evenly among the factors to facilitate interpretation (Gorsuch, 1983).

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Factors may or may not be correlated, depending on the type rotation chosen. Orthogonal rotated factors are uncorrelated and tend to be easier to interpret because they do not require "complicated explanatory hypothesis" (e.g., higher-order factors) (Tinsley & Tinsley, 1987, p. 421). However, orthogonal factors may not be representative of a complex reality. The varimax criterion is the most popular method for orthogonally rotated factors. Varimax seeks to rotate the axis to maximized variance across all the factors within the matrix (Gorsuch, 1983).

Oblique factor solutions produce factors that are correlated and present more complicated views of reality and require a more elaborate interpretation of the factors as well as the latent dimensions underlying the correlation among the factors (Tinsley & Tinsley, 1987). The use of an oblique factor solution implies the existence of higher-order factors. As Gorsuch (1983) states,

> 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)

The most respected oblique rotation uses a promax criterion which seeks to place the axis where the factor matrix has the best least-square fit (Gorsuch, 1983).

In oblique rotation, the factors are correlated, which means the factor correlation matrix is not an identity matrix, **I**. An identity matrix is defined as a matrix which when multiplied by another matrix (e.g., **X**) yields the original matrix, **X**, with no changes in the entries in the original **X**. A matrix with ones on the

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diagonal and zeroes everywhere else is an **I** matrix, e.g., a correlation matrix with all factors having no correlation with each other is an **I** matrix.

Since the factor pattern coefficients and structure coefficients equal:

$$\mathbf{P}_{VxF}\ \mathbf{R}_{FxF} = \mathbf{S}_{VxF},$$

when factors are correlated, as in oblique rotation, the pattern and structure matrices differ more as the factor correlations increase in magnitude.

This also means that in oblique rotation more parameters must be estimated than in orthogonal rotation, since in orthogonal rotation $\mathbf{R}_{FxF}$ is not estimated, and $\mathbf{P}_{VxF} = \mathbf{S}_{VxF}$. Since fewer parameters are estimated in orthogonal rotation, the structure is more parsimonious, and thus all things equal in theory is more replicable.

Higher-order Factor Analysis

The interpretation of factors requires the researcher to be creative, imaginative, and acquainted with the data (Tinsley & Tinsley, 1987). Higher-order factors are derived from the correlations between the lower-level factors. It is possible to continue to derive higher-order factors until there is only one factor (a "g" factor) or the remaining factors are uncorrelated (Gorsuch, 1983). Thompson (1990) describes the difference between first and second-order factors as,

> The first-order analysis is a close-up view that focuses on the details of the valleys and the peaks in the 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

> the range. Both perspectives may be useful in facilitating understanding of the data. (p. 579)

Figure 1 presents an example of the hypothetical higher-order factor structure of the WISC-III.

Insert Figure 1 About Here

When interpreting hierarchical factors, the temptation to interpret from first-order factors should be avoided and higher-order factors should be interpreted in relation to the original variables. As Gorsuch (1983) stated,

> To avoid basing interpretations upon interpretations of interpretations, the relationships of the original variables to each level of the higher-order factors are determined. Then the interpretations are based upon relationships with variables as well as the relationships to the primary factors; for example, a higher-order factor may be found to have a higher relationship to a particular variable than it does with any of the primary factors. Interpreting from the variables should improve the theoretical understanding of the data and produce a better identification of each higher-order factor. (p. 245)

Interpreting factors from factors increases the likelihood of making error. Wasserman, Thompson, and Matula (1993) describe interpreting higher-order factors from first-order factors as "...likened to interpreting shadows (second-order factors) made by other shadows (first-order factors) caused by real objects (the actual variables)" (p. 9).

Another reason to interpret from the original variables is to investigate the extent to which the original correlations can be reproduced from a knowledge of only the higher-order factors. For example, the first order-factors may be a narrow area of generalization. But it is possible that the original correlation matrix may also be reproducible from the broader higher-order factors as well as from the first-order factors.

Two methods have been developed to interpret hierarchical factors and "...to avoid basing interpretations upon interpretations" (Gorsuch, 1983, p. 245). In one procedure the first-order factors are postmultiplied by the second-order factors. The resulting matrix, called a product matrix, is interpretable (Gorsuch, 1983). This product matrix can then be rotated to the varimax criterion (Thompson, 1990). Table 1 provides an example of a rotated product matrix.

Insert Table 1 About Here

One may be able to envision this process by thinking of a microscope with several lenses of greater and lesser magnifying power. The first-order factors "see" the data with most powerful magnification and the greatest detail. The researcher combines the first lens with a second lens (through a multiplicative process) and similar to adjusting the focus, both lenses (matrices) are rotated to "bring into focus" the <u>original data</u> with a new set of higher-order factors. Through this process researchers are able to examine second-order factors against the original variables as well as the first-order factors.

The second method proposed by Schmid and Leiman (1957) takes "an oblique factor analysis solution containing a hierarchy of higher-order factors into an orthogonal solution which not only preserves the desired interpretation characteristics of the oblique solution, but also discloses the hierarchical structuring of the variables" (Schmid & Leiman, 1957, p. 53). This procedure is accomplished by extracting the highest-order factors (or a single "g" factor). The next lower level of factors are then residualized of all the variance contained in the higher-order factors. As Wasserman et al. (1993) note, "...the residualized first-order factors show what's left of the first-order factors, give the presence of the second-order factors" (p. 18).

Table 2 presents a Schmid and Leiman solution where the highest factor solutions are listed first and the primary factors last. The first-order factor entities are uncorrelated to the next highest level of factors (Gorsuch, 1983). This process allows the investigator to examine the amount of variance accounted for by each observed variable at each factor level. As Gorsuch (1983) notes,

> Not only is the latter orthogonalization a possible solution, it is also a desirable one. In science, the concern is with generalizing as far as possible and as accurately as possible. Only when the broad and not so broad generalities do not apply to a given situation does one move to the narrowest, most specific level of generality. (p. 249)

Insert Table 2 About Here

Example Study

As previously stated, one valuable use of factor analysis is the discovery of the components that make up a construct. In this example study, 615 students completed an instrument that consisted of 38 items. The instrument was designed to measure attitudes and beliefs thought to be related to time perspective. Factor analysis was performed using the program SECONDOR (Thompson, 1990). Figure 2 represents a possible factor structure of time perspective for such an inquiry.

Insert Figure 2 About Here

The first table provided by SECONDOR is the correlation matrix of the items (38 items X 38 items). The prerotation eigenvalues of the correlation matrix are also provided (Thompson, 1990). The program's default selects factors with eigenvalues $\geq$ 1.0, which resulted in 10 first-order factors. SECONDOR provides three sets of first-order factor analysis matrices: unrotated, varimax-rotated (orthogonal rotation), and promax-rotated (oblique rotation). The postrotation trace and communality coefficients are provided as well (Thompson, 1990). SECONDOR ultimately provides both a rotated and unrotated product matrix (first-order matrix times the second-order matrix) and Schmid-Leiman solution.

In the example study, first-order factor analysis produced 10 factors. For factor interpretation both the promax-rotated pattern and structure coefficients were examined. The best description of Factor I was Delayed Gratification, which would be a trait of future perspective. Factor II was named Risk/Sensation Seeking and is indicative of a present orientation. Factor III could be called Not Dwelling on the Past, which is unclear regarding time perspective. Factor IV suggests Fatalism, that suggests a present perspective. Factor V could be called Long Term Goals (future perspective). Factor VI suggested attitudes of Short Term Planning (future). Factor VII could be named Commitment to Meet Obligations (part future and past perspectives). Factor VIII could be called Focus on the Present. Factor IX could be called Preference for the Past. Factor X could be named Hedonism, a present perspective.

A higher-order factor analysis was conducted on the 10 factors and produced 4 second-order factors. The original first-order factor matrix (38 variables BY 10 factors) was multiplied by the orthogonally, rotated second-order factor matrix (10 first-order factors BY 4 second-order factors) to produce a product matrix (38 variables BY 4 second-order factors). To further assist in interpretation, the 38 BY 4 product matrix was again rotated to the varimax criterion.

The first second-order factor A could be called Present-Fatalistic Perspective. The second factor could be called Future Perspective. The third second-order factor could be named Present-Hedonism. Factor D could be called Past Perspective.

The data in Table 2 provide an example of the different perspective provided by Schmid and Leiman's solution of "orthogonalizing" the factors. The 4 higher-order factors are listed first followed by the 10 primary factors. As would be expected, a greater amount of the factor variance is accounted for by the second-order factors. In the example data, second-order Factors A, C and D suggest attitudes thought to be of a present orientation, Factor B refers to attitudes suggestive of a future orientation.

Factor II, a first-order factor, suggests a present-oriented, Risk/Sensation Seeking factor. The second-order Factor D while also suggestive of a present orientation more broadly describes seeking immediate gratification and pleasure. The first-order factor IV, suggests a focus on the present from a fatalistic view (i.e., useless to think ahead because life is controlled by fate). Second-order factor C, also suggests a focus for the present but not from a fatalistic reference but from a worry-free attitude toward the past and future.

From the examples provided the utility of Schmid and Leiman solution is clear. The ability to examine the data from different perspectives allows researchers to better define constructs and understand data more fully.

Conclusion

The use of higher-order factor analysis allows researchers in the behavior sciences to examine data from different levels and perspectives. This can provide a better understanding of the data (Gorsuch, 1983; Thompson, 1990). However, not all researchers advocate the use of second-order factor analysis (Nunnally, 1978, Tinsley & Tinsley, 1987). As Nunnally (1978) states,

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

Nunnally's feelings regarding the desire for parsimony and the potential for misinterpretation are understandable. When available, simple results would always be the first choice of any researcher. However, that is rarely the case. If the goal of research is to understand and know as much of our reality as possible, then behavior scientists must be willing to use complicated constructs. Higher-order factor analysis can be a powerful tool in the exploration and development of complex theories.

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Table 1

Varimax-Rotated Product Matrix and h^2

Variable	First-Order Solution I	II	III	IV	h^2
V1	-.207	-.041	**-.391**	-.233	.251
V2	-.094	**.534**	.086	.070	.307
V3	**-.610**	.176	-.182	-.149	.459
V4	.132	-.183	**-.605**	-.044	.419
V5	-.214	**.492**	-.279	.047	.368
V6	.049	**.648**	-.118	.064	.440
V7	.071	**.597**	.235	-.016	.417
V8	**-.476**	.163	-.145	**-.372**	.413
V9	-.123	**.468**	-.075	.051	.243
V10	-.089	.053	**-.397**	-.278	.245
V11	.106	-.164	-.268	**-.501**	.361
V12	.133	.030	-.136	**-.377**	.179
V13	-.042	**.517**	.101	-.180	.312
V14	**-.368**	.108	.004	**-.454**	.354
V15	-.039	**.646**	.042	-.132	.438
V16	-.269	**.465**	.072	-.133	.312
V17	**.577**	.060	-.055	-.263	.409
V18	.189	**.321**	-.024	-.220	.188
V19	-.029	-.065	-.127	**-.509**	.281
V20	-.071	-.020	**-.550**	**-.315**	.408
V21	.044	-.016	-.083	**-.516**	.276
V22	.045	.078	.166	**-.535**	.322
V23	-.087	**.562**	-.264	.007	.393
V24	-.132	**.429**	**-.347**	.023	.323
V25	**.596**	**.301**	**-.341**	-.019	.563
V26	.086	**.381**	.059	**-.355**	.282
V27	.067	.063	-.188	**-.449**	.245
V28	.034	**.559**	.026	.039	.316
V29	-.007	-.208	-.080	**-.411**	.219
V30	.163	-.025	**-.361**	**-.390**	.310
V31	-.067	.105	.013	**-.332**	.126
V32	.144	**.639**	.142	.003	.449
V33	**.512**	.024	.129	-.333	.390
V34	-.081	-.017	-.126	**-.445**	.221
V35	-.120	**.526**	.093	.141	.320
V36	.023	**.389**	-.005	-.237	.208
V37	.102	**.473**	.046	-.042	.238
V38	.172	**.526**	-.113	.164	.345
	2.565	4.877	1.863	3.039	12.344

Note. Data from Thomas (1993). Bold print represents variable loadings $\geq |.30|$.

Table 2

Schmid-Leiman Solution for the ZTPI (n=615)

	Second-Order Solution				First-order Solution										
	A	B	C	D	I	II	III	IV	V	VI	VII	VIII	IX	X	h^2
V1	.117	-.107	**-.304**	**-.366**	-.022	**.459**	-.045	.083	.002	.009	-.097	.011	.069	-.173	.516
V2	-.160	**.513**	-.124	.044	.043	.004	.035	.094	.069	**.463**	.018	.039	.040	-.013	.541
V3	**-.336**	.098	**-.335**	**-.473**	.038	.068	**-.387**	.187	.118	-.036	-.019	-.076	.114	-.034	.685
V4	**.405**	-.288	-.409	-.066	.022	-.053	.058	.097	.285	-.265	.216	-.071	.011	-.048	.640
V5	-.076	**.388**	**-.450**	-.098	.023	.052	-.065	-.060	**.468**	.048	-.018	.005	-.024	.006	.601
V6	.043	**.592**	-.282	.089	.188	.083	.038	.037	.244	.253	-.011	.019	-.051	-.025	.613
V7	-.065	**.633**	.065	.088	**.326**	-.028	-.012	.008	-.055	.136	-.152	.004	.032	.014	.570
V8	-.154	.139	-.184	**-.579**	.085	.031	-.051	.043	-.034	.077	.005	-.111	.469	-.052	.667
V9	-.099	**.416**	-.244	-.015	.051	-.009	-.046	-.046	**.491**	.066	.024	.148	-.015	.078	.523
V10	.228	-.001	-.283	**-.336**	.017	.017	-.024	.019	-.092	-.077	.041	**-.513**	.041	-.009	.528
V11	**.423**	-.132	.019	**-.405**	.034	.036	-.001	.182	-.181	-.237	-.076	-.272	.064	.049	.572
V12	**.325**	.067	.045	-.259	-.044	**.337**	.018	.107	.080	-.054	-.159	.057	-.108	.057	.360
V13	-.020	**.542**	-.006	-.133	.072	.031	.059	-.035	-.080	.032	**-.502**	.045	.080	-.023	.591
V14	-.101	.140	.017	**-.569**	.060	.122	.024	-.116	-.018	-.041	-.133	-.028	**.445**	.004	.605
V15	-.015	**.646**	-.105	-.096	.151	.005	.014	-.049	.039	-.009	**-.454**	.006	.034	-.005	.672
V16	-.203	.459	-.100	-.223	-.065	-.126	-.101	-.105	.105	.025	-.254	-.226	-.001	.120	.494
V17	**.585**	.135	.201	.088	.027	-.006	**.460**	-.066	-.050	.050	-.066	.007	.084	.057	.645
V18	.241	**.352**	.025	-.069	**.373**	.106	.107	-.021	.135	-.035	.076	.074	.173	.022	.411
V19	.253	-.017	.075	**-.459**	-.048	**.401**	-.002	-.027	.009	-.015	.011	-.206	.003	.093	.496
V20	**.331**	-.097	-.376	**-.384**	-.131	.078	.072	.091	.150	-.015	.093	-.269	.084	-.007	.555
V21	.291	.047	.122	**-.417**	-.211	-.002	.133	.109	.003	.120	.006	-.191	.101	.180	.443

V22	.183	.194	**.316**	**-.389**	-.117	-.014	.008	.127	.080	-.038	-.162	.035	.042	.257	.455
V23	.031	**.475**	**-.404**	-.057	.135	-.088	-.026	-.076	.201	-.064	-.181	-.210	-.016	-.021	.548
V24	.031	**.323**	**-.458**	-.087	-.076	-.030	.044	-.012	.135	.150	-.126	-.231	-.022	-.064	.446
V25	**.619**	.271	-.185	.267	.116	-.047	.299	.084	.024	.003	-.109	-.115	-.177	-.036	.733
V26	.178	**.439**	.094	-.222	.029	.063	.041	.057	.029	-.109	**-.486**	.109	.001	.078	.559
V27	**.326**	.093	-.004	**-.361**	-.015	.051	-.066	**.525**	.000	.132	.019	.078	.020	.076	.558
V28	-.021	**.540**	-.132	.079	**.329**	-.139	-.048	-.025	.132	-.030	-.056	-.065	.025	.026	.473
V29	.213	-.157	.125	**-.365**	-.044	**.563**	.017	.014	-.074	.022	-.040	.037	.010	-.021	.547
V30	**.459**	-.030	-.118	-.291	.020	.008	-.060	**.531**	-.080	.018	.042	-.080	-.047	.023	.613
V31	.078	.147	.076	**-.304**	.075	-.288	.022	.241	-.005	-.018	-.018	.077	**.319**	.088	.389
V32	.024	**.657**	-.009	.130	.275	-.016	-.021	.102	.017	.198	-.114	-.008	-.087	.033	.597
V33	**.481**	.145	**.371**	.022	.192	.096	.052	.104	-.013	-.131	.052	-.061	-.201	.205	.556
V34	.184	.015	.024	**-.431**	.087	**.582**	-.045	-.034	.068	.012	.062	-.051	.037	.013	.583
V35	-.214	**.494**	-.147	.089	.033	-.008	.037	.050	.025	**.513**	.065	-.039	.031	-.031	.596
V36	.108	**.410**	-.021	-.167	.213	.093	-.010	-.067	-.060	.164	.139	**-.447**	-.001	.091	.524
V37	.061	**.479**	-.043	.048	**.443**	.075	.019	-.086	.016	-.035	-.042	-.024	.105	-.044	.464
V38	.099	**.472**	-.241	.234	**.396**	-.091	.002	.133	-.075	.061	-.077	-.039	-.011	-.138	.564
Trace	2.56	4.88	1.86	3.04	1.09	1.36	.54	.87	.84	.88	1.06	.95	.72	.028	20.93

Note. The column after the orthogonalized matrix presents the sum of the squared entries in a given row. The first 4 columns represent the second order factors. The next 10 columns represent the first order solution, based on variance orthogonal to the second order (Gorsuch, 1983, pp. 248-254). Bold print represents variable loadings $\geq |.30|$.

Figure 1

Construct of Intelligence as measured by the WISC-III

Third-order factor	Intelligence	
Second-order factors	Verbal Abilities	Performance Abilities
First-order factors	Information Similarities Arithmetic Vocabulary Comprehension	Picture Completion Picture Arrangement Block Design Object Assembly Coding

Figure 2

Hypothetical structure of Time Orientation

Third-order factor		Time Orientation	
Second-order factors	Future	Past	Present
First-order factors	Goal setting Planning Perseverance Time Press Daily planning Pragmatic action for later gain	Social Commitment Historic Past Personal Past	Fatalistic Hedonistic Avoid planning