AN EXAMINATION OF MEASUREMENT ASSUMPTIONS REQUIRED BY CONFIGURATIONAL CONSISTENCY THEORY: A SIMULATION

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ABSTRACT

AN EXAMINATION OF MEASUREMENT ASSUMPTIONS REQUIRED BY CONFIGURATIONAL CONSISTENCY THEORY: A SIMULATION

By

Barbara Earlene Jackson Davis

This study was concerned with the accuracy with which attribute values can be reconstructed or obtained by using a multidimensional scaling procedure on a relational matrix. Relational matrices were simulated under conditions in which the dimensionality of the matrices varied, relations contained error, and the precision of the measurement scale varied. The results of the simulation indicated that the rank of the relational matrix effected the recovery of the attribute values. The recovery of the attribute values were also influenced by the precision of the measurement scale.

AN EXAMINATION OF MEASUREMENT

ASSUMPTIONS REQUIRED BY

CONFIGURATIONAL CONSISTENCY

THEORY: A

SIMULATION

By

Barbara Earlene Jackson Davis

A THESIS

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To my husband, Clyde, for his
loving devotion and to my parents,
Russell and Gladys Jackson for
their many prayers.

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INTRODUCTION

An important theoretical perspective in modern social psychology is called consistency theory (Abelson et al., 1968). This "theory" is not really a theory at all but a collection of partial theoretical formulations (Festinger, 1957; Osgood and Tannenbaum, 1955; Abelson and Rosenberg, 1958; Newcomb, 1953; Cartwright and Harary, 1956; Heider, 1958; and Phillips, 1967) which share the common theme that man has a need to maintain consistency among his attitudes, beliefs, and behavior. One such formulation is Phillips' (1973) configurational consistency theory (CCT). This theory differs from other consistency formulations in three important respects: (1) it is more completely axiomatized than others; (2) it provides explications of the meaning of consistency over a range of cognitive complexity; (3) it provides a rationale for a multidimensional scaling procedure that can be applied to attitudinal data. In the following pages, points (1) and (2) will be briefly discussed in preface to a more detailed examination of point (3). This examination will focus on the measurement assumptions of configurational consistency theory (CCT) and relative to these assumptions, the accuracy with which the multidimensional scaling may be accomplished as a function of errors of measurement and precision of the measurement scale.

REVIEW OF LITERATURE

Configurational consistency theory assumes a dimensional organization of cognition. Cognitions are represented in CCT as elements which have descriptive properties called attributes. These attributes are assumed to index some position on a set of bi-polar scales which function as attribute dimensions. Examples of such bipolar scales are good-bad, sweet-sour, strong-weak, active-inactive, etc. Therefore, the organization of a person's attribute space is some discrete number of dimensions and each cognitive element has a position on each dimension. That is, an element is assigned to a fixed point in some attribute space (Phillips, 1973). Such a dimensional characterization of cognition is similar to that of Osgood and Tannenbaum (1955) and Scott (1963).

In addition to elements and attributes, a third important theoretical term in CCT is the concept of a relation. This notion is similar to Heider's (1958) notion of a sentiment or a unit relation. A relation, varying continuously in value between +1 and -1, is assumed to exist between any given pair of elements. Relations are assumed to be symmetrical, that is, the relation between i and j is the same as the relation between j and i. A relation in CCT is the link between elements.

The theory assumes that two elements are mutually consistent if the relation between them is equal to a weighted sum of the products of the scale values of the two elements on all critical attribute dimensions (Phillips, 1973).

Another feature of CCT is that it provides an explication of consistency for the complex person as well as for the simple person. Other consistency formulations are unable to do this. CCT accomplishes this feature by allowing for multiple attribute dimensions. The definition of cognitive complexity in terms of dimensionality is a common one (Bieri, 1968; Scott, 1963). CCT, however, provides a method for determining this dimensionality or complexity of a cognitive structure through the analysis of the relational configuration of that structure. This relational configuration can be represented as an nxn matrix. A relational matrix can be obtained as a first order datum from a set of judgments. If configurational consistency holds, an index of complexity or dimensionality can be determined by finding the rank of the relational matrix. Configurational consistency is thus given a formal definition in this context: "If, for a cognitive structure of complexity m, the associated relational matrix is of rank m—where the rank of a matrix is just an index of its dimensionality—then the structure is configurationally consistent." (Phillips, 1973).

An important special case of consistency theory is the unidimensional model. The unidimensional model of CCT assumes that any judged relational matrix is of rank 1. If a relational matrix is of rank 1, then consequently the person who made the relational judgments was using only one evaluative dimension. If the relational matrix is not rank 1 then the relational matrix would be considered to be inconsistent. The degree of inconsistency could be measured by the departure from rank 1. This unidimensional model is just the balance model proposed by Phillips (1967) of which the Abelson and Rosenberg balance model is a special case. Balance theory is thus just the special unidimensional case of CCT. Balance theory conflicts with complexity because balance requires the rank of the relational matrix to be one. This is a conflict because if a relational matrix is complex then its rank will be greater than one and balance theory doesn't allow the rank of the relational matrix to be greater than one. CCT allows the rank of the relational matrix to be equal to the complexity of the cognitive structure. Since CCT allows for people of different complexities, it is a potentially more useful formulation of consistency.

As previously noted, CCT provides a rationale for multidimensional scaling that can be applied to attitudinal data. Attribute values can be derived from a relational matrix by computing the characteristic vectors of the judged relational matrix. Phillips (1967) has shown that the dominant characteristic vector of such a matrix can be empirically identified with global evaluation.

The multidimensional scaling requires the assumption that the judged relational values of the relational matrix were made on a ratio scale. A ratio scale is required because the characteristic vectors of a matrix are unique up to multiplication by a constant, that is, if C is a characteristic vector of R than αC is a characteristic vector of αR if and only if α is a scalar.

Even though CCT seems to be a potentially more useful formulation of consistency, there are problems with the measurement assumptions required by it. The process by which a relational matrix is obtained is by asking a person to make judgments on certain elements. The values assigned to these judgments are obtained scores. From a psychometric point of view, obtained scores are equal to true scores plus some random error. Random error may be thought of as noise. The measurement problem faced by CCT is the inaccuracy in recovering attribute values from the relational matrix. This inaccuracy may be produced by the rank of the relational matrix, the precision of the measurement scale, and random noise in the system.

The rank of the relational matrix is defined as the dimensionality of the configuration from which the relational matrix is formed. In a study of multidimensional scaling, Young (1970) found that accuracy in recovering scale scores was affected by rank. This unexpected finding was not accounted for by Young.

Another reason for expecting accuracy to be a function of rank derives from the numerical methods used to recover latent variables. For example, the computer program Eigort, which is the basis for the present analysis of latent vectors decreases in accuracy as rank increases. Those two facts provide a basis for the hypothesis that the rank of a relational matrix will contribute to the inaccuracy in recovering attribute values.

Precision of the measurement scale means the coarseness or fineness of the scale. Precision of the measurement scale may contribute to the distortion of true scores in a relational matrix, thereby adding to the inaccuracy in recovering attribute values.

Noise was defined as random error. Noise may affect the accuracy in recovering attribute values because the greater the noise the greater the distortion of true scores.

With these concepts in mind, it was decided to investigate the effects of rank of relational matrix, precision of measurement scale, and noise in the system on obtaining attribute values from relational matrix.

The issue of error in measurement is not unique to this study. Young (1970) discussed some issues of measurement involved in metric scaling. Young used a simulation to examine measurement error. He did five replications.

Young was concerned with metric determinacy which is the degree of success in obtaining a ratio scale from data without ratio properties. The variables investigated in Young's study were (1) the number of points in a configuration, (2) the dimensionality of the underlying real configuration, and (3) the amount of error contained in a set of data. Young's results suggested that the degree of metric determinacy was influenced by the dimensionality of the configuration. The one dimensional configuration produced the highest degree of metric determinancy. The two dimensional configuration produced the second highest degree of metric determinancy and the three dimensional configuration produced the lowest degree of metric determinacy. Young's study indicated that metric determinacy decreased as the error was increased.

For a better explanation of the multidimensional scaling process for recovering attribute values a two dimensional cognitive structure will be considered. A two dimensional cognitive structure has two nxl vectors corresponding to its attribute space. Each vector multiplied by its transpose generates an nxn matrix. With the two dimensional cognitive structure, there would be two matrices. The sum of these two matrices is the relational matrix. The process discussed above is satisfactory from a theoretical point of view. However in the case of an empirical study of multidimensional scale, what would be the values of the main diagonal?

These values were assumed to be 1's in Phillips (1967) study. A better procedure than just assuming the diagonal values to be 1's might be to estimate the values. This can be accomplished by finding the characteristic vectors of the relational matrix with 1's in the diagonal, then square each value of the two largest characteristic vectors (two dimensional structure). The sum of these products is used in the diagonal instead of the 1's. Then the characteristic vectors for the relational matrix with the new diagonal values are computed. This process continues until the difference between the values in the main diagonal differs from the new computed diagonal values by only some specified small amount.

The issue in this thesis is the accuracy with which attribute values can be recovered from a relational matrix, under conditions in which the dimensionality of the structure varies, relations contain error, and the precision of the measurement scale varies.

STATEMENT OF PROBLEM

This study is concerned with the accuracy with which attribute values can be reconstructed or obtained by using a multidimensional scaling procedure on a relational matrix. Configurational consistency theory assumes that the values of a judged relational matrix are true scores. However, in empirical situations the values of the judged relational matrix are obtained scores. This study simulates the obtained scores for the relational matrix to see if the correct attribute values can be reconstructed. From a psychometric point of view, obtained scores are true scores plus some distorting effect due to error. The distortion of the true score is thought of as a combination of dimension of relational matrix, random noise, and precision of measurement scale.

The simulation generates relational matrices of different sizes. It generates true score relational matrices and obtained score relational matrices. Even though the true values of the diagonals of the true score relational matrices are known, the simulation puts 1's in the diagonals and estimates the correct diagonal values. In the simulation, the obtained score is influenced by the precision of the measurement scale and random noise.

The dependent variable is the cosine of the angle between the simulated true score relational matrix's characteristic vectors and simulated obtained score relational matrix's characteristic vectors and the cosine between repeated obtained scores. If the cosine is one, then the two vectors are the same. Thus vectors are more similar if the cosine of the angle between them is high. A main effect due to noise and rank is expected because of Young's (1970) study and the computer program Eigort.

METHOD

Simulation Study

Three (3) 3x3x3x2 factorial designs were used for the simulation. One factorial design was for 5x5 matrices, one was for 7x7 matrices and one was for 9x9 matrices. The first factor was the rank or dimensionality of the relational matrix--rank 1, rank 2, or rank 3. The second factor was the precision of the measurement scale used--3 point, 7 point or 11 point scale. The third factor was three different levels of random noise--level 1 -.09 to +.09, noise level 2 -.19 to +.19, and noise level 3 -.29 to +.29. The fourth factor was repeated measures on the third factor.

In order to arithmetically simulate an nxn matrix of rank r, random numbers were generated and used to construct r 1xn true evaluative vectors which were orthogonal to each other. Next each of those 1xn vectors were multiplied by their transpose--producing r matrices. Then, those resulting matrices were added together to produce an nxn true relational matrix of rank r. Next a noise matrix of the same size (nxn) was generated with its values being restricted to a certain interval such as -.09 to +.09. This noise matrix was added to the true nxn relational matrix. The noise matrix was an operational definition of random error in the system. This is due to the usual psychometric assumption that obtained score is equal to true score plus random error. Another noise matrix at the same level of noise as the first was generated for the same nxn true relational matrix.

A second source of measurement error was distortion due directly to the precision of the measurement scale. The nxn matrix of rank r with noise level l was deliberately distorted by adjusting it to a k point scale. This was accomplished by rounding values of each cell of the nxn matrix off to the nearest tenth place as associated with the scale being used. For an example: if a 5 point scale (+1, +.5, 0, -.5, -1) were being used and a value of the true relational matrix was -.3; then if it were associated with the 5 point scale its value would have been -.5.

After all of the nxn matrices with rank r and noise level l added were adjusted to different measurement scales, the characteristic vectors and roots were computed. They were computed on a computer program called MAT. This program estimated the correct diagonal values for each nxn matrix. This was accomplished by finding the characteristic vectors of the relational matrix with 1's in the diagonal, then squaring each value of the significant characteristic vectors. The sum of those products was used in the diagonal instead of the 1's; next the characteristic vectors for the relational matrix with the new diagonal values were computed. This process continued until the difference between the values in the main diagonal differed from the new computed diagonal values by some specified small amount. The MAT program had a subroutine called Eigort which computed the characteristic vectors and roots. The Eigort program recovered the characteristic vectors for a rank 1 matrix perfectly, but for the rank two and three matrices the Eigort program did not recover the characteristic vectors as perfectly as it did for the rank one matrices. This fact was discovered when the Eigort subroutine was tested with matrices for which the characteristic vectors were known. The error in computing the characteristic vectors for the rank two and rank three matrices was attributed to the rounding off procedure used in Eigort. Nevertheless, it was the best program available for computing characteristic vectors and roots of matrices.

Next the cosines were obtained between the simulated true score vector and the simulated obtained score vector. After that the cosines between the repeated simulated obtained score was computed. All matrices were distorted due to a particular precision of measurement scale except for the true relational matrix.

The cosines between the repeated (independent replication) measures served as a measuring device in determining the amount of error in the system when we did not have true scores. This measure was analogous to a test-retest reliability measure. Thus, it was possible to determine the magnitude of main effects and interactions of rank of relational matrix, amount of noise in the system, and scale precision in obtaining attribute values from a relational matrix.

RESULTS

The dependent variables were the average cosine between simulated true score vectors and simulated obtained score vectors and the cosine between repeated simulated obtained score vectors. The results from the simulated true scores and simulated obtained scores are presented first, after which the results from the repeated simulated obtained scores are presented.

An ANOVA was performed on each different size of matrix individually with rank of relational matrix, noise level, and precision scale as the factors. For the 5x5 matrices the analysis on the true score cosines indicated that there was a main effect due to rank of the relational matrix ($p<.0001$) (see Table 1). A Newman-Keuls test indicated that rank 1 matrices had significantly higher cosines than matrices of greater dimensionality ($p<.05$). The ANOVA indicated that for the 5x5 matrices there was a significant interaction of rank and precision. A Newman-Keuls test indicated that the combination of rank one with intermediate precision (7 point scale) and rank one with high precision (11 point scale) had significantly higher cosines than any other combination of rank and precision.

For the 7x7 matrices there was a main effect due to the precision scale ($p<.0001$). High and intermediate precision had significantly higher cosines than did low precision. There was a main effect due to rank for the 7x7 matrices. Rank one matrices had significantly higher cosines than did matrices of higher dimensionality. The analysis also suggested that there was a significant interaction of noise and precision. A Newman-Keuls test indicated that the combination of low noise with high precision had significantly higher cosines than any noise level with low precision and better than intermediate noise with intermediate precision. The combination of intermediate noise and high precision had significantly higher cosines than low noise and low precision. Other combinations of noise and precision were not significantly different. There was also another significant interaction for the 7x7 matrices and that was the combination of rank and precision. The combination of low rank with both intermediate and high precision had significantly higher cosines than any other combination of rank and precision ($p<.05$). There was no significant difference between the combination of low rank with intermediate precision and low rank with high precision.

For the 9x9 matrices there was a main effect due to the precision scale ($p<.0001$). High and intermediate precision scales had significantly higher cosines than did low precision scale ($p<.05$). Another main effect for the 9x9 matrices was the rank of the matrix ($p<.0001$). The ANOVA suggested that for the 9x9 matrices that there was a significant interaction of rank and precision. By performing further analysis it was indicated that the combination of low rank with either intermediate or high precision had a significantly higher cosine than did any other combination of rank and precision ($p<.05$).

The comparisons of simulated matrices with true score indicated that rank (for all different size matrices) and precision (for 7x7 and 9x9 matrices) were main effects. Rank one matrices (for all size matrices) had significantly higher cosines than matrices of higher dimensionality. Intermediate and high precision (for 7x7 and 9x9 matrices) had significantly higher cosines than low precision. Significant interactions were also observed. The interaction of rank and precision was significant for all size matrices. The combination of low rank with either intermediate or high precision had significantly higher cosines than any other combination of rank and precision for all size matrices. The interaction of noise and precision was only significant for the 7x7 matrices. There was no main effect due to noise for any of the different size matrices.

Next an ANOVA was performed on the repeated simulated obtained scores. For the 5x5 matrices there was a significant interaction of all three factors.

For the 7x7 matrices there was a main effect due to precision scale. Low precision scale had significantly higher cosines than intermediate or high precision scales

($p<.05$). The analysis also suggested that there was a main effect due to rank. Rank one matrices had higher cosines than matrices of greater dimensionality ($p<.05$). Rank two matrices had higher cosines than rank three matrices.

The analysis suggested that for the 9x9 matrices that there was a main effect due to rank. After performing the Newman-Keuls test, it was indicated that rank one matrices had significantly higher cosines than did rank two or rank three matrices. There was a main effect due to noise. Low noise matrices had significantly higher cosines than matrices which had either intermediate or high noise. Low precision scale matrices had significantly higher cosines than intermediate or high precision.

The analyses of the repeated scores indicate that there was a main effect due to the rank of the relational matrix (for 7x7 and 9x9 matrices). Both rank one 7x7 and 9x9 matrices had significantly higher cosines than matrices of higher dimensionality. Also for the 7x7 matrices the rank two matrices had significantly higher cosines than rank three matrices. There was a main effect due to precision for the 7x7 and 9x9 matrices. The 7x7 and 9x9 matrices with low precision scale had significantly higher cosines than those with intermediate or high precision scale.

The 5x5 matrices had a significant interaction of all factors rank, precision, and noise.

The analyses suggest that for both the true score and repeated measurement comparisons there were main effects due to rank. The analyses indicate that for both sets of data that the rank one matrices had significantly higher cosines than matrices of greater dimensionality. Both sets of data also had a main effect due to precision. The matrices with the intermediate or high precision scales for the true score comparison had significantly higher cosines than matrices with low precision scales. This was just the opposite effect found in the repeated score comparison where the matrices with the low precision scale had significantly higher cosines than matrices with intermediate or high precision. There was no main effect due to noise for the true score comparison and only one of the matrices, 9x9, in the repeated measures comparison had a main effect due to noise.

The true score data showed a significant interaction of rank and precision--low rank with intermediate or high precision had significantly higher cosines than any other combination of rank and precision. There was an interaction effect of noise and precision for the 7x7 true score data. The only significant interaction for the repeated score data was a significant three way interaction of all the factors for the 5x5 matrices.

DISCUSSION AND SUMMARY

The major issue in this thesis was the accuracy with which attribute values can be recovered from a relational matrix, under conditions in which the dimensionality of the structure varies, relations contain error, and the precision of the measurement scale varies. Analyses were performed on the different sizes of matrices separately because the size of the matrix was not one of the factors under investigation. The different size matrices were only used for the purpose of generality.

The results of the comparisons of the relational matrices indicate that the rank of a relational structure does effect the accuracy of the recovery of the attribute values. This was expected because of the results of Young's (1970) study and the computer program Eigort. Low rank relational matrices recovered attribute values better than matrices of higher rank.

For the true score matrices, the 7x7 matrices and the 9x9 matrices had a main effect due to precision. Both set of matrices had significantly higher cosines with intermediate or high precision than with low precision. The results suggest that for a unidimensional model of consistency, intermediate or high precision would be necessary. This was due to the interaction of rank one with intermediate or high precision. This implies that Phillips (1967) would have obtained significantly better support for his model if he had used a finer precision scale than the three point scale he used.

Neither the 7x7 repeated score matrices nor the 9x9 repeated score matrices had any significant interactions. Both the 7x7 and the 9x9 repeated score matrices had main effects due to rank and precision. This time the precision scale with the highest cosine was the low precision scale. This is in opposition to the true score matrices where intermediate or high precision scales produced significantly higher cosines than low precision scale.

Table 1. Summary of Analysis of Variance for 5x5 Matrices with True Scores.

Source	SS	DF	MS	F
A (Precision of Measurement Scale)	.1426	2	.0713	.5451
B (Noise Level)	.6012	2	.3006	2.2974
C (Rank of Relational Matrix)	6.3662	2	3.1831	24.3289*
AB	1.1124	4	.2781	2.1253
AC	1.5896	4	.3974	3.0377*
BC	.3632	4	.0908	.6940
ABC	.4872	8	.0690	.5274
Exp Error	14.1304	108	.1308	

*Significant at $p<.05$

Table 2. Means Table 5x5 Matrices with True Scores.

AC (Precision X Rank)

	R1	R2	R3
PS1	.486	.440	.176
PS2	.811	.320	.227
PS3	.879	.207	.233
Marginal Means	.725	.322	.223

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APPENDICES

Table Al. Summary of Analysis of Variance for 7x7 Matrices with True Scores.

Source	SS	DF	MS	F
A (Precision of Measurement Scale)	1.2740	2	.6370	12.6739*
B (Noise Level)	.0872	2	.0436	.8668
C (Rank of Relational Matrix)	4.0570	2	2.0285	40.3619*
AB	.5232	4	.1308	2.6027*
AC	1.0468	4	.2617	5.2066*
BC	.0808	4	.0202	.4025
ABC	.5456	8	.0682	1.3572
Exp Error	5.4216	108	.0502	

*Significant at p<.05

Table A2. Means Table for 7x7 Matrices with True Scores.

	AB (Precision x Noise)		
	N1	N2	N3
PS1	.152	.209	.244
PS2	.386	.278	.378
PS3	.557	.442	.315

Table A3. Means Table for 7x7 Matrices with True Scores.

	AC (Precision X Rank)			
	R1	R2	R3	Marginal Means
PS1	.280	.242	.082	.202
PS2	.652	.186	.202	.347
PS3	.781	.282	.248	.437
Marginal Means	.572	.237	.178	

Table B1. Summary of Analysis of Variance for 9x9 Matrices with True Scores.

Source	SS	DF	MS	F
A (Precision of Measurement Scale)	1.5220	2	.7610	16.1332*
B (Noise Level)	.0778	2	.0389	.8250
C (Rank of Relational Matrix)	3.7970	2	1.8985	40.2497*
AB	.1352	4	.0338	.7163
AC	1.1668	4	.2917	6.1850*
BC	.1452	4	.0363	.7698
ABC	.3872	8	.0482	1.0220
Exp Error	5.0868	108	.0471	

*Significant at $p<.05$

Table B2. Means Table 9x9 Matrices with True Scores.

AC (Precision X Rank)

	R1	R2	R3	Marginal Means
PS1	.271	.188	.154	.205
PS2	.693	.313	.204	.403
PS3	.804	.232	.312	.449
Marginal Means	.589	.244	.223	

Table C1. Summary of Analysis of Variance for 5x5 Matrices with Repeated Scores

Source	SS	DF	MS	F
A (Precision of Measurement Scale)	.5964	2	.2982	3.2221
B (Noise level)	.8612	2	.4306	4.6529
C (Rank of Relational Matrix)	4.5112	2	2.2556	24.3732
AB	.4836	4	.1209	1.3061
AC	1.2560	4	.3140	3.3925
BC	.2528	4	.0632	.6835
ABC	1.5936	8	.1967	2.1253*
Exp Error	9.9900	108	.0925	

*Significant at $p<.05$

Table C2. Observed Cell Means for 5x5 Matrices Repeated Scores

Rank	Noise	Scale	
1	1	1	.905
1	1	2	.896
1	1	3	.954
1	2	1	.940
1	2	2	.795
1	2	3	.794
1	3	1	.372
1	3	2	.910
1	3	3	.857
2	1	1	1.000
2	1	2	.355
2	1	3	.370
2	2	1	.270
2	2	2	.370
2	2	3	.425
2	3	1	.352
2	3	2	.191
2	3	3	.274
3	1	1	.646
3	1	2	.479
3	1	3	.425
3	2	1	.854
3	2	2	.444
3	2	3	.227
3	3	1	.645
3	3	2	.336
3	3	3	.332

Table D1. Summary of Analysis of Variance for 7x7 Matrices with Repeated Scores.

Source	SS	DF	MS	F
A (Precision of Measurement Scale)	1.5564	2	.7782	9.5890*
B (Noise level)	.2958	2	.1479	1.8223
C (Rank of Relational Matrix)	6.6388	2	3.3194	40.9002*
AB	.5740	4	.1435	1.7681
AC	.3404	4	.0851	1.0484
BC	.6520	4	.1630	2.0090
ABC	.8240	8	.1030	1.2696
Exp. Error	8.7588	108	.0811	

*Significant at $p<.05$

Table D2. Means Table for 7x7 Matrices with Repeated Scores.

A (Precision)		
PS1	PS2	PS3
.709	.498	.472

Table D3. Means Table for 7x7 Matrices with Repeated Scores.

C (Rank)		
R1	R2	R3
.849	.516	.311

Table E1. Summary of Analysis of Variance for 9x9 Matrices with Repeated Scores.

Source	S	DF	MS	F
A (Precision of Measurement Scale)	3.7688	2	1.8844	25.3010*
B (Noise Level)	1.4484	2	.7242	9.7231*
C (Rank of Relational Matrix)	3.7760	2	1.9980	26.8256*
AB	.2320	4	.0580	.7782
AC	.4040	4	.1010	1.3563
BC	.6828	4	.1707	2.2918
ABC	.6528	8	.0816	1.0950
Exp Error	8.0352	108	.0744	

*Significant at p<.05

Table E2. Means Table for 9x9 Matrices with Repeated Scores.

A (Precision)		
PS1	PS2	PS3
.780	.399	.461

Table E3. Means Table for 9x9 Matrices with Repeated Scores.

B (Noise Level)		
N1	N2	N3
.693	.470	.476

Table E4. Means Table for 9x9 Matrices with Repeated Scores.

C (Rank)		
R1	R2	R3
.787	.393	.460