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ABSTRACT

New ways of using factor analysis in research designs are suggested in this paper that would allow research to move in new directions that are being suggested for educational technology. A brief simplified overview of factor-analytic techniques is given, followed by a description of some recent developments in factor-analytic techniques which make it more useful to the researcher. In addition, certain trends in instructional technology research that seem to require multivariate statistical techniques are examined. Finally, several studies are used to illustrate the various variations of factor analysis, and to show how the techniques can tap into structural as well as performance-based aspects of cognition. (HAB)

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FACTOR ANALYSIS: A TOOL FOR INSTRUCTIONAL TECHNOLOGY RESEARCH

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At a time when research methodology is being critically questioned (Snow, 1974; Clark and Snow, 1975), it is appropriate to look around us at research designs and statistical techniques which are untried, unusual, new, or which have been tried and abandoned. Admittedly, factor analysis as it is generally used does not really fit into any of these categories. However, in the following pages ways of using it are suggested which are all of these four things. The studies cited as illustrations of the methods presented apply factor analysis in new and unusual ways, and also resurrect and elaborate upon methods which have not been used for the last ten years. In this way, factor analysis allows research to move in the new directions that are being suggested for educational technology.

There is no doubt that factor analysis is a complicated statistical procedure. It has a tendency to frighten people off, and the small group of superspecialists in the area tends, by virtue of the complexity of their mathematics and their reliance on computers, to be beyond the reach of the general researcher (Nunnally, 1975). This paper therefore begins with a brief simplified overview for those not too familiar with factor-analytic techniques. Those more familiar with the various procedures discussed, and my "superspecialists" who come across this paper will, I hope, forgive any oversimplification. But it is hoped that those with only a superficial knowledge of factor analysis will nonetheless be able to get some ideas of how it can be applied profitably to research. Next, some recent developments in factor - analytic

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techniques are discussed, which make it more useful to the researcher. Then, certain trends in instructional technology research which seem to require multivariate statistical techniques are examined. These are linked to the notion of cognitive structure itself becoming grist to the researcher's mill. Finally, several studies are used to illustrate the various variations of factor analysis, and to show how the technique can tap into structural as well as performance-based aspects of cognition.

Factor analysis: an overview

Factor analysis is a method of simplifying matrices of intercorrelations among sets of variables. To do this, the technique identifies clusters of variables that are highly correlated among themselves, and uses these to describe more fundamental variables, or dimensions, in the domain from which the original variables were taken. These fundamental variables are called factors. Not only does factor analysis identify basic factors in a set of intercorrelated variables, but it also calculates the strength of the relationship between each variable and each factor. This measure is the variable's "loading" on the factor, and functions in a way similar to a correlation coefficient.

The variables in the original intercorrelation matrix can be any variables for which correlation coefficients, covariances or other measures of association can be calculated. Historically, these variables have usually been tests within test batteries, and factor analysis of the intercorrelations among the tests has been used to search for and

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identify various dimensions within human intelligence, whether a single general intelligence factor (Spearman, 1904), more complex hierarchical arrangements of human intellectual abilities (Burt, 1948; Vernon, 1961), or a complete model of the structure of the human intellect (Guilford, 1956; Guilford, 1967). Its use is by no means limited to this area, however. Factor analysis has been used to describe the structure of associative meaning within a set of interrelated words (Deese, 1962, 1965), to study basic dimensions underlying the phenomenon of aphasia (Jones and Wepman, 1961), and even to identify certain basic chemical phenomena associated with the hardening of cement (Woods, Steinour and Starke, 1932).

A useful way of looking at factors is to think of them as vectors in a defined space. (More commonly, this idea is applied to correlation between two variables, when a correlation coefficient is described as the cosine of the angle between two lines representing the strength and the direction of each variable.) In the case of factor analysis, the factors, as vectors, can be moved about an axis through the space in which they lie, and can thus be moved from their original location to a position which provides a more parsimonious description of the relationships between variables and factors. This procedure of relocating factors (vectors) is known as "rotation". This may be done in one of two ways. Either the factors are specified to be uncorrelated, in which case the vectors remain at right angles to each other as they are rotated. Or the factors can themselves be intercorrelated. In this case, the angle between the vectors is not constrained to be ninety degrees. The factor matrices which result from rotation are said to be

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orthogonal if the factors are uncorrelated, and oblique if the factors are correlated.

In simplifying and describing intercorrelation data, factor analysis gives us several kinds of information either directly stated in, or which can be derived from, factor matrices. These statistics are as follows:

A number of factors. The number of factors extracted by factor analysis can be specified either by the researcher directly, or indirectly by specifying values of other statistics, such as the minimum eigenvalue to be accepted for a factor, the accuracy of the factor solution, and so on. For reasons that will become apparent, it is often more meaningful for the researcher to specify the number of factors to be extracted indirectly rather than directly, since differences in the number of factors needed to describe interrelationships between a set of variables are themselves of interest.

Factor patterns. Factors are described and named in terms of the variables that load highly on them. In a matrix, a pattern of high loadings is apparent which describes the structure of the intercorrelations between factors and variables.

Factor loadings. These are the individual values of the relationships between each variable and each factor.

Common factor variance. Also known as the communality of each variable, this statistic (the sum of the squared loadings) indicates how much of the variance of each variable can be accounted for by the factor loadings.

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Sometimes this is discussed in terms of the variance not accounted for by the factors - unique factor variance -- which is quite simply the communality subtracted from one.

Interfactor correlations. These are indications of the interrelationships between the factors themselves. They are either zero, for orthogonal solutions, or non-zero for oblique solutions.

These five statistics provide interesting descriptions of the structural properties of sets of sets of interrelated variables. However, purely descriptive information is of little use to statistically-based research. Factor matrices can describe structures very well, but have not been able to say if one structure is significantly different from another; at least, not until recently. Thanks largely to the development of computers, it is now possible to perform the immensely lengthy and complicated computations which are needed to use factor analysis for hypothesis testing.

Hypothesis testing with factor analysis.

Confirmatory factor analysis, described by Mulaik (1972, pp.361-401), allows the researcher to test the structure of a set of intercorrelated variables against a pre-determined model of factor structure. A researcher can state an hypothesis concerning the structure of the interrelationships in question, and can convert this hypothesis into a factor model by assigning predetermined values to some, or to all of the five statistics that factor analysis provides. For example, he may hypothesize that, within a set of interrelated variables, there are three basic factors, with loadings of certain values in certain positions,

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with a certain proportion of the common variance accounted for by the three factors, which are themselves interrelated in a certain way. The techniques of confirmatory factor analysis allow him to test the actual observed data against the hypothetical model, and to estimate the goodness of the fit of the model to the data. The goodness of fit is indicated by a large-sample chi-square value. If the chi-square value is significant, then it is probable that there is not a good fit between the data and the model, and the hypothesis should be rejected. A non-significant chi-square indicates a good fit, and the researcher should conclude that any apparent deviations of the data from the model are due to chance, and that the hypothetical model provides an adequate description of the structure of the data.

A further refinement of confirmatory factor analysis is simultaneous factor analysis (Joreskog, 1971). With this procedure, confirmatory factor analysis can be performed in more than one population at once. Although this method was developed to identify factor models common to two or more populations by estimating the goodness of fit to both simultaneously, with care the technique can be used to test for differences in the structure of interrelationships among identical sets of variables in two or more populations. First, the researcher factor-analyzes the intercorrelation matrix of variables in one of the populations. He takes the values obtained for each of the five statis-tics as his hypothetical model, and then factor analyzes both populations simultaneously. A significant chi-square indicates a significant

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departure of the second population from the model based on the first population, and the researcher can conclude that the interrelationships among the variables are different in the two populations.

Joreskog offers a further refinement to his method. By starting out with a general factor model, and gradually making it more specific, it is possible not only to discover whether the two sets of data are structurally different, but also to isolate that particular statistic in which the difference occurs. This is helped considerably by the hierarchical nature of the statistics. For example, differences in factor loadings do not necessarily imply differences in factor pattern, but will always imply differences in common factor variance. The researcher begins by testing the most general model which states that the number of factors is invariant. He then tests the more restricted model of the invariance of factor pattern, then common factor variance, then interfactor correlation. If he finds that the factor patterns are the same for both populations, but then that common factor variances are different, he can conclude that the number of factors, and factor patterns are the same in both populations, but that common factor variance and interfactor correlations are different. Each successive hypothetical model is a specific instance of the preceding one.

Trends in Educational Technology Research.

The descent from the rarified atmosphere of factor analysis theory to the down-to-earth problems of instructional technology research is not as precipitous as it might at first seem. Recent pleas by

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researchers have suggested that research become more representative of real-world situations. Stowe (1973) suggests both the systems approach and research as methodologies for education. While the latter would not be superceded by the former, the systems approach would nevertheless broaden the scope of the educational researcher. A systems approach to researchable problems would mean conducting research in the classroom rather than in the laboratory. Variables often excluded by experimental control would be included in analysis, perhaps at the expense of statistical precision and high levels of significance. Research designs would become more representative of classroom environments and would allow proximal and distal variables to enter into research designs and analysis (Snow, 1974). Indeed, Clark and Snow (1975) have proposed research designs that allow for experimental control without limiting representativeness, that have both internal and "ecological" validity.

It is not difficult to see why these more representative and realistic research methodologies are so appropriate to educational technology research. The educational technologist is concerned first and foremost with systems, whether of media, machines and resources, teachers, facilities and students, or complex interrelationships of learner characteristics. The study of systems of any type requires the acknowledgement of complexity. If, in a system, a part is isolated from the other parts, the system breaks down. Educational technology researchers cannot therefore afford to look at things in isolation, but must, as Snow says, look at peripheral variables as well. The integration of learning resources into optimum learning environments

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requires a holistic approach to research and development.

Similarly, if complex learning environments are to be exploited to their fullest with learners, the learners themselves must be treated holistically as well. Winn (1975) drew attention to the fact that the learner is a complex system of many interrelated variables. To the learning situation, the learner brings not merely prior learning, but feelings, unrelated associations, opinions, attitudes and so on. It seemed appropriate to Winn to consider the learner as functioning cognitively in a way analogous to an open system. A model of learning, built around this analogy, allows for the effect of peripheral environmental variables upon the more central variables of learning.

One common thread underlies all of these suggestions and analogies. If educational technologists want to study the effects of richly varied learning environments on the whole learner, then they must take into consideration whole systems of variables both within and outside the learner. Aptitude-treatment interaction research is a sign that researchers recognize that learners differ on many dimensions, and the technique has produced many interesting findings, which are already giving rise to some useful generalizations (Allen, 1975). However, in a truly representative learning situation, even assigning small groups of students to different instructional treatments on the basis of defined and researched aptitudes is not really going far enough. Ideally, each variable affecting each learner as an individual should be accounted for. Obviously, this is logistically impossible at present. However, the educational technologist can begin moving in this direction if he studies

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many variables in single subjects rather than just a few variables in many subjects.

The study of many variables in combination in learners has two implications: the researcher needs to obtain data on the learner's cognitive structure rather than just performances; such structural information, because it involves many variables, must be analyzed by multivariate techniques. Moreover, the researcher needs to be able to use multivariate techniques to test statistical hypotheses about differences between various structures, and changes in them. Among the several available multivariate techniques, factor analysis provides the necessary structural information, and in its confirmatory and simultaneous forms is capable of testing hypotheses about these structures and differences between them. Deese's studies of the structureof associative meaning (Deese, 1962, 1965) are good examples of how factor analysis can describe structural relationships between concepts. The factor matrices emerging from the analysis of intersection coefficients derived from free associations to groups of related words provided detailed descriptions of the way the concepts named by the words were related. Deese's technique, modified to suit the more recent developments in confirmatory and simultaneous factor analysis, provides avery useful jumping-off point for the study of cognitive structure. In some instances, confirmation of the results obtained from factor analysis is possible through analysis of variance and multiple regression techniques. This confirmation is useful to validate factor analysis as a method of testing hypotheses.

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Factor analysis and cognitive structure.

Factor analysis can only provide meaningful data to the researcher if he has some idea of what it is in human cognition that the various statistics derived from factor analysis represent. It is intuitively appealing to suppose that, since factor analysis provides information about structural interrelationships between variables, factor matrices represent cognitive structure in some way. If this were so, then the researcher could indeed test hypotheses about changes in the way in which subjects structure the information they receive, not just the way they perform on tests. Cognitive structure itself would then become a dependent variable. But for this come about, the researcher must be able to answer such questions as, "What is a factor?", "What do significant differences in common factor variance mean in terms of how a subject structures information?" Fortunately, answers to some of these questions can be found in the literature.

Scott (1966) suggests that the number of factors extracted by factor analysis under certain specified procedures serves as a satisfactory measure of domain differentiation. This is a property of cognitive structure which indicates the degree to which a person distinguishes among the elements in a given cognitive domain. For example, if one subject arranges objects in a given domain in such a way that five factors are extracted from the intercorrelations between the objects, the researcher can conclude that this subject has a more complex differentiating structure than a subject for whom nnly four factors are obtained.

A more elaborate picture of cognitive structure is offered by

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MacNeill (1974). Like Scott's report, MacNeill's paper also offers possibilities for relating factor matrices to cognitive structure. MacNeill identifies two main components of cognitive structure: discriminating structure, which refers to the breaking-down of information into its components for sorting; and integrating structure, which refers to how the partitioned parts are related. (It is impossible to overlook the parallel between discriminating and integrating structures, and Piaget's "assimilation" and "accommodation", (Piaget, 1967). The complexity of a person's cognitive structure depends upon the complexity of both the discriminating and the integrating components. Discriminative complexity is a function of the number of dimensions in a person's cognitive structure and of the articulation of those dimensions. If a dimension is considered to be like a scale on which people rate items, then the articulation of the dimension is a function of the number of possible gradations on the dimension. Integrative cognitive complexity is a function of the relationships between the dimensions. A person's discriminative complexity increases as the number of dimensions and the number of gradations on them increases, and integrative complexity increases as the dimensions become less correlated to each other.

Parallels between this conception of cognitive structure and factor matrix statistics are easily seen. Again, it is intuitively appealing to think of factors derived from the interrelationships between concepts to represent the dimensions of cognitive structure, factor loadings to be related to articulation, and interfactor correlations to describe degrees of integrative cognitive complexity. If the relationship

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between factor patterns and cognitive structure could be proven to exist in fact, this would be most useful to educational technology researchers. It would allow them to study the impact of multivariate learning environments on the cognitive structure of individual learners and of groups of learners, and arrive not just at assessments of the effectiveness of instruction on learner performance, but also on how the learners structure the information in the first place.

Experimental evidence.

Two studies have just been completed which attempt to relate the various statistics provided by a factor matrix to cognitive structure and learning, (Winn, 1976a, 1976b). Beginning from Shavelson's (1972) study showing that instruction leads to better-defined cognitive structures, a first study set out to compare factor matrices obtained from interrelated concepts obtained before and after instruction in that domain from which the concepts were taken. If factor analysis can indeed reveal cognitive structure, then, according to the theory of cognitive complexity, factor matrices should reflect changes in complexity as a result of instruction. More specifically, instruction should bring about an increase in the number of factors, and an increase in the loadings matched by an increase in common factor variance as a result of increased discriminative complexity, and it should also bring about a decrease in interfactor correlations as a result of increased integrative complexity.

These hypotheses were tested as follows: Subjects were pretested in semantics at the beginning of an introductory communications course.

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At the same time, they made single free verbal associations to twelve words naming key concepts in the semantic area. These associations were used to compute intersection coefficients measuring the association between the concepts, and these coefficients were factor-analyzed. This procedure replicated exactly Deese's (1962, 1965) method of studying associative meaning. After the three weeks normal course-work, which comprised the "semantics unit" in the course, the subjects were post-tested on semantics and made a second set of free associations to the same words. These too were factor analyzed. Pre-and post-test comparisons of the test scores showed that the subjects had learned a significant amount about semantics.

The two factor matrices derived from the associations made before and after instruction were compared using Joreskog's simultaneous factor analysis of several populations procedure, described earlier in this paper. Although no significant differences were found between the number of factors and the factor patterns of the two matrices, the matrix obtained from the post-instruction associations had significantly larger common factor variances and significantly smaller interfactor correlations. These two significant differences lend credence to cognitive complexity theory, and also to the ability of factor analysis to reveal cognitive structure. The lack of differences between the two matrices as far as the number of factors and factor patterns were concerned was not surprising in view of the generally low factor loadings in both matrices. The unique factor variances were much larger than the common factor variances in both matrices, and this means that the factors that were

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extracted accounted for only a small portion of the total variance. This phenomenon is also true in Deese's work, incidentally, and is probably attributable to the low probability of similar associations being made to different words, even if the words are judged to be highly related conceptually. It seems, however, that that amount of variance accounted for by factors, and interfactor correlations, are related to learning, and one can conclude, perhaps, that learning brings about cognitive structures of greater integrative complexity and greater "structuredness".

A second study was conducted to explore further the relationships between factor structure as a measure of cognitive structure and performance. In this second study two measures of performance were used. The first of these, as in the previous study, was the subject's score on a written test. The second performance measure was the mean number of word associations each subject gave to the stimulus words. This second measure was chosen as a dependent variable because it was seen as an indication of a subject's familiarity with and access to the content and not necessarily the accuracy with which he knew it.

After normal classroom instruction in audiovisual communication, which was the next segment in the introductory communications course used in the first study, students made multiple free associations to ten words naming ten new key concepts. This was a modification of Deese's procedure developed by Winn (1976c) in another study. At the same time, the subjects took their midterm exam. Their performance on those questions directly related to the ten key words was noted, as was the mean number of words

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each subject gave as associations to the stimulus words. Intersection coefficients for the ten stimulus words were calculated for each subject, and these were factor analyzed. In this way, factor matrices were obtained for every individual subject. The number of factors, the mean common factor variance, the percentage of variance accounted for by the first factor, and the percentage of variance accounted for by all of the factors were noted from the factor matrices of each subject. These statistics were then used as predictors of midterm test performance and of the mean number of associations made by each subject. Multiple regression of these variables on midterm score and number of associations showed a significant positive relationship between mean common factor variance and midterm score, and between all of the predictor variables and number of associations made. A significance level of .059 was also obtained for the relationship between midterm score and the percentage of variance accounted for by the first factor.

This second study provides further evidence of the relationship between cognitive structure measured by factor analysis and performance. The relationship between common factor variance and performance on the midterm test was not unexpected, and serves to support the similar finding in the first study. The near-significance of the relationship between the midterm score and the percentage of variance accounted for by the first factor alone requires further experimental study. This is all the more necessary since the relationship between the percentage of variance accounted for by all the factors and midterm score was no where near significant. This suggests that there is quite a complex relationship

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between performance on the test and the cumulative variance accounted for by successive factors. An interaction effect between performance and cumulative percentage might well exist.

The significant negative correlation between mean number of associations given to the stimulus words and the number of factors seem to contradict cognitive complexity theory. The more associations a subject makes to a set of interrelated words, the fewer the number of factors which account for the common meaning. If factors correspond to dimensions in cognitive structure, the opposite should occur. There are two points that need to be made. The first concerns the idea that the more associations that are made, the more overlap there must be. While it is true that the probability of repetition increases as the number of responses increases, it is also true that the number of unique responses increases as well. It seems unlikely, therefore, that the repetition of certain responses accounts for the smaller number of factors. A more plausible explanation seems to be that fluency of association is somehow related to simplicity of associative structure. In this case, those subjects who are able to structure a cognitive domain with the help of just a few dimensions would be able to give more associations to key words from that domain. Access to the various dimensions of the domain would be easier for them. Simplicity of cognitive structure leads to greater familiarity with the content of that structure. However, this simplicity does not seem to help performance on a test based on the content. There was no significant relationship between the number of factors and performance on the midterm test. Neither, incidentally,

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were the two dependent variables, test performance and number of associations, significantly related.

A significant positive relationship between common factor variance and the number of associations made should cause no surprise. It confirms, for number of associations as a measure of subject performance, what the first study and the other part of this study showed for test performance. The more associations that are made, the more the variance can be accounted for by the common factors.

The relationships between the percentages of variance accounted for by the factors and the mean number of associations for each stimulus word seem to be as complex as the relationships between these percentages and midterm test performance. There was a significant negative relationship between the total percentage of variance accounted for by the factors and the number of associations made, and a significant positive relationship between the percentage of variance accounted for by the first factor and the number of associations made. The interaction between factor position, amount of variance accounted for by the factor and number of words given as associations is difficult to interpret without further study. However, the greater the number of words, the greater the percentage of variance accounted for by the first factor, and the smaller the percentage of variance accounted for by all the factors. It seems that cognitive simplicity is accompanied by a markedly unequal distribution of the common factor variance among the factors. As subjects make more responses, they not only use fewer dimensions to structure the cognitive domain in question, but the importance of the most important dimension

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is much greater than that of the others.

The results of these two studies can be generalized only with caution. It seems that common factor variance is a good indicator of performance on a written test of a cognitive domain. The more a person knows about something, the more the common meaning of the concepts within the domain can be accounted for by the fundamental dimensions along which the person structures his knowledge of the domain. Beyond this, the amount of variance accounted for by the most important of these dimensions also seems to be a good predictor of test performance, though the reasons for this can only be speculative with the amount of data furnished by these two studies. There appear to be stronger relationships between the number of associations given and cognitive structure. Simplicity of structure seems to enable the learner to make associations more easily, and suggests an easier access to the information in his cognitive structure. Common factor variance, too, is closely related to the number of associations given, and there also appears to be a relationship, though a complex one, between the order of factors, the amount of variance they contribute, and the number of words given as associations. Generally, the various statistics given by factor analysis seem to behave as cognitive complexity theory predicts they should, although there appears to be a stronger relationship between these statistics and quantitative measures, such as the number of associations made, than quantitative measures, such as test performance.

It appears then that factor analysis is capable of describing certain aspects of cognitive structure. Just where does it fit into

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research in educational technology? The obvious advantage that the technique has over other more traditional methods of data analysis is that factor analysis permits the researcher to assess the impact of various instructional treatments on how learners process and structure information, not just on how they perform on tests of that information. If the values attached to the various statistics derived from factor analysis are used as dependent variables in a research study, then the researcher will be able to observe structural changes in the learner as a result of various instructional treatments. These structural changes, moreover, will be attributable to the action of many variables, not just a few, if free association data are used.

An example of the use of factor analysis in this way is a study by Winn (1976c) of the structural differences in free associations to words, black-and-white and color pictures. Subjects made multiple free associations to monochrome and to color pictures, and to the corresponding noun labels. The intersection coefficients between the sets of stimuli were factor analyzed, and the three matrices were compared using Joreskog's technique. It was found that the common factor variances of both monochrome and color pictures differed from those of the nouns, but that the factor patterns were the same. It was concluded that the basic cognitive structures derived from pictures and words are the same, but that words lead to a tighter structuring of information than pictures. The shapes of the structures are the same for both words and pictures, but the shapes and more clearly defined in the case of words. These results allowed the researcher to draw conclusions about differences between the

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qualitative and the quantitative effects of different ways of presenting information. Factor analysis provided information about the qualitative aspects of the structures which would not have been available as a result of more traditional forms of analysis.

A second experiment in the same study allowed Winn to isolate two color factors in the analysis of associations to colored stimuli. This showed that color does indeed have an effect on the way in which learners structure information, when color is used to differentiate concepts within a conceptual domain. Here again, factor analysis in the confirmatory mode allowed structural information to be studied where more conventional techniques would not have proven adequate.

Clearly, these few studies are primitive. The complex techniques associated with the use of factor analysis in these and similar experimental settings have to be refined to some extent. However, the analysis of free associations by the various techniques discussed above does provide an "access route" to cognitive structure. There is a need for researchers in the educational technology area to apply these techniques to the study of the effectiveness of different instructional treatments on different learners. We need information about the learner-as-system, and factor analysis can give it to us. Nor should the researcher limit himself to the analysis of free associations. Deese's technique has limitations. It is hard to imagine that freely associating to stimuli allows the subject to reveal everything he knows and feels about something. Other methods of deriving profiles of the structure of a particular cognitive domain need to be developed. Digraph analysis of instructional content (Frase, 1969; Kingsley, Kopstein and Seidel, 1968)

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and adjacency matrix construction (Harary, Norman and Cartwright, 1965) both offer to extend the intercorrelation of concepts in a given domain away from single-word responses towards connected discourse. Other types of factor analysis need to be explored as well. Particularly promising is longitudinal factor analysis (Evans, 1967) as a technique for comparing structures in a "before and after" experimental design. Other multivariate techniques should not be overlooked either. An example of multiple regression used in conjunction with factor analysis has already been given. Its usefulness to the educational technology researcher is not to be underestimated.

In conclusion, factor analysis is useful to the educational technology researcher chiefly because it provides qualitative information about a learner's cognitive structure. Recent developments in the technique allow it to be used for hypothesis testing and for the comparison of structures derived from different treatments, and derived before and after treatments. In this way it is particularly useful for telling us about the way learners process and arrange the information they receive without excluding any of the peripheral variables that inevitably influence cognition. Experiments have shown that the various statistics derived from factor analysis of free association data do indeed act as predicators of some kinds of learner performance, and, by following the predictions of cognitive complexity theory, they have been shown to provide information about the learner's cognitive structure. Clearly, the experiments reported above need to be replicated. It is far too early to place great confidence in the validity of factor analysis as a measure

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of cognitive structure. But what has been done so far suggests that this is an area worthy of further study, and that, applied to the study of differences in cognitive structures derived from different instructional treatments, factor analysis is indeed capable of becoming one of the educational technologist's most valuable research tools.

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