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CONVERTING TEST DATA TO COUNSELING INFORMATION

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ABSTRACT

Part 1: Rationale

Information from tests, when considered in the context of decision theory, can play an important role in vocational development. This role is primarily one of stimulating and facilitating exploratory behavior. Objective procedures for converting test data into counseling information are discussed and illustrated with special attention being given to similarity (centour) scores and similarity score profiles. Alternative names emphasizing the guidance use of these procedures are suggested, i.e., *exploration indices* and *exploration maps.* The similarity score profiles, when used in conjunction with success estimates, avoid many of the pitfalls inherent in Parsonian approaches to test interpretation.

Part 2: Field Trial with Feedback

A computer-based system incorporating the above data-information conversion procedures was developed and field tested with potential vocational school students. Longitudinal validation analyses involving more than 1,500 students and 20 interest and aptitude measures provided the empirical base for the data-information conversion procedures. Similarity scores and success estimates were developed for each of the 12 vocational program areas in which the students enrolled. These reporting procedures were then field tested with an additional group of 900 students enrolled in 12 high schools. Illustrations of the similarity score reporting procedures and student reactions to them are provided.

CONVERTING TEST DATA TO COUNSELING INFORMATION[1]

Dale J. Prediger

PART 1: RATIONALE

This report is concerned with objective procedures for converting test scores and other data into information which is relevant to a counselee's educational and vocational plans, decisions, or problems. Validity studies are crucial to data-information conversion procedures. However, these studies as usually reported, are of little direct help to the counselor who has a student and a set of test scores before him. While it is true that an accumulation of validity studies performed within a theoretical framework may support various uses of a particular test, the task of converting a counselee's test scores into usable information is left undone. Typically, the counselor can find the standing of a counselee in some norm group; after that, he is on his own. Professional knowledge, clinical judgment, and personal sensitivity always will play crucial roles in test interpretation. However, objective data-information conversion procedures can make the counselor's job much easier. Just what *does* a percentile rank of 63 on the XYZ Mechanical Aptitude Test say to the student and his counselor?

Local Validity Data and Decision-Making

Almost 15 years have passed since Dyer (1957) made a convincing case for local studies of test validity. Dyer was only one of a host of measurement specialists who cautioned test users about accepting tests on the basis of face validity or assuming that one or two validity studies conducted in some other setting provide sufficient evidence that a test would be useful in their setting and for their purposes. Recent reviews of validation research (Ghiselli, 1966; Prediger, Waple, & Nusbaum, 1968) have reinforced this caution.

An excellent discussion of the role of local validity data in vocational guidance and decision-making has been provided by Clarke, Gelatt, and Levine (1965). In their discussion, attention was focused on the process of decision-making, with

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[1]With minor modifications, Part 1 of this report will appear as an article in Volume 18 of the *Journal of Counseling Psychology* under the title "Data-Information Conversion Procedures in Test Interpretation." Part 2, also with minor modifications, will appear as an article in the *Journal of Educational Measurement* under the title "Converting Test Data to Counseling Information: System Trial—with Feedback."

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information on the possible outcomes of various courses of action being seen as a necessary if not sufficient condition for wise decisions. Examples of local validity studies were given to illustrate the development of objective probabilities useful in educational planning. As with Dyer, use of experience (expectancy) tables was emphasized. Subsequent articles (Gelatt & Clarke, 1967; Katz, 1966, 1969; Thoresen & Mehrens, 1967) elaborated on the role of objective probabilities in decision-making, the influence of objective probabilities on subjective probabilities, and the interactions among subjective probabilities, choice option utilities, and personal values.

Katz (1963, 1966), in particular, was careful to show how the decision-making process is related to the broader process of vocational development. Results from the massive Project TALENT validation studies also have been placed firmly within the context of vocational development theory and decision theory (Cooley & Lohnes, 1968). We have passed the era in which the Parsonian concept of test interpretation could be viewed as the epitome of educational and vocational guidance. However, the above studies and formulations leave little doubt about the continued importance of test information, when properly validated, in the vocational-development process.

Bridges between Data and Information

Goldman (1961) described three objective bridges between test scores and their meaning for the counselee: the norm bridge, the regression bridge, and the discriminant bridge. Most of our current data-information conversion procedures consist of some form of the norm bridge. As Goldman noted, the norm bridge is an incomplete bridge since test norms simply permit one to estimate standing in some group and do not, per se, indicate the implications of this standing. The regression bridge, however, is a complete bridge from test scores to their implications and, as such, readily lends itself to data-information conversion. Usually, the implications are in the form of success predictions obtained via experience tables or regression equations.

The third bridge noted by Goldman, the discriminant bridge, provides an objective measure of a counselee's *similarity* to various criterion groups. Discriminant analysis techniques, when combined with the similarity score procedures developed by Tiedeman, Bryan, and Rulon (1951), permit the comparison of a counselee's test results with those of various criterion groups along the major dimensions of test data that differentiate the groups. The complementary nature of similarity and success estimates was first discussed 20 years ago (Rulon, 1951; Tiedeman et al., 1951). Few counselors, however, are familiar with the characteristics of *similarity (centour) scores* or their potential role in test interpretation. These topics have received little attention in testing texts or test interpretation manuals. For this reason, an illustration is provided in the following section.

Data-Information Conversion via Similarity Scores

Consider the information needs of Fred, a high school student thinking about enrolling in a vocational-technical education program. Similarity score procedures applied to Fred's high school grade record and test scores could result in a report indicating Fred's similarity to successful and satisfied students in various programs. In the example that follows, the similarity scores shown in parentheses after each of the vocational programs are on a scale ranging from 0 to 100 with 100 represen-

ting the highest degree of similarity. The closer Fred's scores on the relevant tests are to the test scores of the *typical* successful and satisfied student in a vocational program, the higher his similarity score will be for that program. Fred's similarity score report might look like this: vocational horticulture (87), carpentry (41), commercial art (28), auto body (26), distributive education (25), auto mechanics (14), radio-TV repair (3), and data processing (1).

Thus, on the basis of the measures used, Fred's aptitudes and interests are most similar to students in vocational horticulture. Carpentry ranks second, and three other programs are in an approximate tie for third. Fred is least similar to students in data processing and radio-TV repair.

In this example, test data have been transformed into information that is directly relevant to one of the major functions of tests in educational and vocational guidance—facilitating exploratory behavior. Fred's counselor might use the similarity scores quite advantageously in stimulating Fred to explore the program options available to him. For this reason, similarity scores might be more appropriately called *exploration indices;* that is, indices which suggest choice options a counselee may want to explore.

Of course, the similarity scores should not be used alone in facilitating exploratory behavior. Their potential value in this example lies in suggesting vocational possibilities that might not have been recognized otherwise. The degree to which Fred explores these possibilities will be a function of his value system and the opportunities provided him.

Complementary Role of Success Estimates

Success estimates obtained from regression analyses or expectancy tables also can be used to facilitate exploratory behavior. For example, Fred might be encouraged to explore the vocational programs for which he is predicted to receive the highest grades. However, estimates of success might be more appropriately incorporated into the actual exploration process where they can be considered in conjunction with a host of other relevant factors. After all, Fred may not place much value on making high grades. His similarity scores could identify vocational programs in which he is similar to "successful and satisfied" enrollees. His probable level of success could then be determined upon further exploration. *Thus, a two-stage strategy is suggested with similarity scores being used to stimulate and facilitate exploration and success estimates being an important consideration during the process of exploration.*

Other considerations also indicate the need for caution in the use of success estimates as the primary basis for facilitating exploration. Consider, for example, an experience table showing the relationship between the scores on some test and grades in carpentry. Could this table be used appropriately with Sally, Fred's sister? Can Sally be considered similar to the group from which the experience table data were obtained? To what degree would the trends shown in the results apply to her? Similarly, to what degree would success predictions in radio-TV repair apply to Fred (similarity score = 3)? Can we legitimately use Fred's test scores to predict lab grades in cosmetology? Or, in another context, are we justified in comparing a high school senior's college freshman GPA predictions in engineering, humanities, education, physical science, or business? These questions, recently discussed by Rulon, Tiedeman, Tatsuoka, and Langmuir (1967), need further investigation. A "reasonable" degree of similarity between counselees and the validation sample might well be an appropriate prerequisite for the use of success estimates in counseling.

A second difficulty with success predictions results from the well-known "criterion problem." Obtaining a suitable criterion of success in education and training is difficult enough, but when one moves into the world of work, the definition and measurement of success become infinitely more complex (Thorndike, 1963; Thorndike & Hagen,

1969). *Members* of various occupations or occupational clusters can be readily identified, however. (Gross criteria for identifying "successful and satisfied" occupational group members can also be applied.) This is all that is needed to permit use of similarity score procedures. Thus, data-information conversion would be possible.

Overcoming the Profile Problem

Judgment of a counselee's similarity to various criterion groups is not new in counseling. Certain commercially available inventories, e.g., the Strong Vocational Interest Blank and the Kuder Occupational Interest Survey, provide scores giving direct aid in the process. However, special test construction and criterion group requirements present formidable barriers to the development of such inventories. In addition, existing inventories cover only one area of measurement, usually interests. Simultaneous coverage of other areas (e.g., aptitudes, aspirations, biographical data) is not practical through use of these special test construction techniques.

Profiles showing the typical performance of various criterion groups often have been provided for other tests and inventories. Counselors are expected to use these profiles by noting the similarity of a counselee's profile to the profiles of the criterion groups. Anyone who has engaged in this process does not need a description of what has long been known as the profile problem (Tiedeman, 1954).

Similarity scores take the guesswork out of profile comparison; but unless they are used in conjunction with discriminant analysis procedures, they fail to deal directly with important aspects of the profile problem, e.g., do the criterion groups actually score differently on the measures involved? If so, what are the important measures and how should they be weighted? Unfortunately, a set of similarity scores can be obtained from purely irrelevant variables.

For the above reasons, discriminant analysis procedures are often used in conjunction with similarity scores. These procedures enable one to determine whether the criterion groups are, in fact, differentiated by the measures. If so, the measures can be weighted and combined into independent *factors (discriminant functions)* that maximize criterion group differentiation. Furthermore, the number of factors needed for criterion group differentiation can be determined. Thus, one may, and usually will, find that two factors account for most of the discriminatory power of a set of measures when applied to criterion groups relevant to educational and vocational counseling. Finally, the nature of the factors can be identified by noting the measures that correlate highly with them.

Equations resulting from discriminant analysis can be used to calculate criterion group positions on the discriminating factors. These positions, in turn, can be plotted on a coordinate grid with the vertical and horizontal axes representing the two major factors. In the same manner, the factor scores of a given student may be calculated and plotted. The student's position on the coordinate grid then may be compared visually with the criterion group positions.

This technique for graphically depicting a student's similarities and dissimilarities was implicit in early work on the profile problem (Tiedeman, 1954) and was specifically suggested more than 10 years ago (Whitla, 1957; Dunn, 1959). However, it has been mentioned only occasionally in the professional literature since then (e.g., Baggaley & Campbell, 1967; Cooley & Lohnes, 1968) and has received little attention in testing texts. Rulon and his colleagues (1967) have provided a detailed discussion of the rationale underlying discriminant analysis and similarity score procedures along with ample illustrations of the resulting graphical solution to the profile problem. However, in presenting the illustrations, emphasis was placed on representing the geometry of the statistical procedures. Little attention was given to test interpretation applications of the illustrations.

The graphical procedures described above can serve several important functions in data-information conversion. Application of these procedures to the problem faced by Fred and his counselor—consideration of vocational program options—is illustrated by the similarity score profile presented in Figure 1. Note that the two dimensions or factors that best differentiate the vocational programs are represented by the axes of the coordinate grid. Each factor is scaled with a mean of 50 and a standard deviation of 10 for students in all vocational programs combined. Of the 10 aptitude and interest measures used in the analysis on which the profile is based, those having factor correlations with an absolute value of .40 or more are listed as factor anchors. (The following symbols are used to indicate level of correlation: ** = $r > .59$; * = r of .50 - .59; no * = r of .40 - .49.)

Fred's factor scores of 56 and 36 for Factors 1 and 2, respectively, have been plotted on the coordinate grid along with the mean scores of the eight vocational programs. (In several instances, e.g., auto body and welding, related vocational programs have been combined into one group.) The ellipse surrounding the vocational horticulture group encloses the factor scores of approximately 50% of the students in the group and is analogous to the scatter diagrams often seen in discussions of correlation. Similar, but not identical, ellipses could be used to represent the scatter of factor scores for the other vocational programs. One ellipse should be sufficient, however, to obtain a good estimate of program overlap.

The size of Fred's similarity scores is reflected in the distances between Fred and the various vocational programs on the profile. Although the relationship of similarity score size to distance is not exact, it is sufficiently high to give a useful visual picture of degree of similarity. For example, Fred's position is quite close to that of the vocational horticulture group, the group for which he received his highest similarity score, i.e., 87. On the other hand, programs for which he has low similarity scores are much farther away.

By comparing Fred's position on the profile with the positions of the various vocational programs, one can obtain valuable insights into the reasons underlying Fred's similarity scores. Field trials with potential vocational school students (Prediger, 1970) have shown this is important, since use of similarity scores by themselves often leaves the counselee with the question, "But why did the scores come out like that?" In Fred's case, we see that both he and the typical horticulture student score only slightly above average on Factor 1, while Factor 2 scores suggest relatively strong artistic interests and relatively low mechanical reasoning aptitude and scientific interests.

Fred may wonder why his similarity score for area H was so low. From the profile, we see that the Factor 2 scores for Fred and area H students are relatively far apart. In addition, the position of area H students on Factor 1 suggests that they have stronger clerical skills and interests than Fred. Similar reasoning can be followed in comparisons with the other groups represented on the profile.

In a sense, similarity score profiles provide the student with a map of an important domain of choice options. In helping Fred understand the possible reasons underlying his similarities and dissimilarities, one is helping him to project certain aspects of his *self* into the choice domain. His position in that domain is shown, and he is encouraged to relate his position and characteristics to those of students who have elected various choice options. This might be viewed as a type of vicarious exploration within the dimensions mapped by the similarity score profiles. Perhaps a more appropriate, guidance-oriented term for these profiles would be *"exploration maps."*

Variation in the characteristics of students who have made a specific choice will be clearly evident from the ellipse shown on the profile (or exploration map). If ellipses are shown for all of the vocational programs, overlap among the various groups also will be evident. Criticisms of counseling applications of trait and factor research sometimes are based on the fact that divergencies within criterion groups and similarities among criterion groups are concealed. Similarity score profiles reveal these facts of life. At the same time,

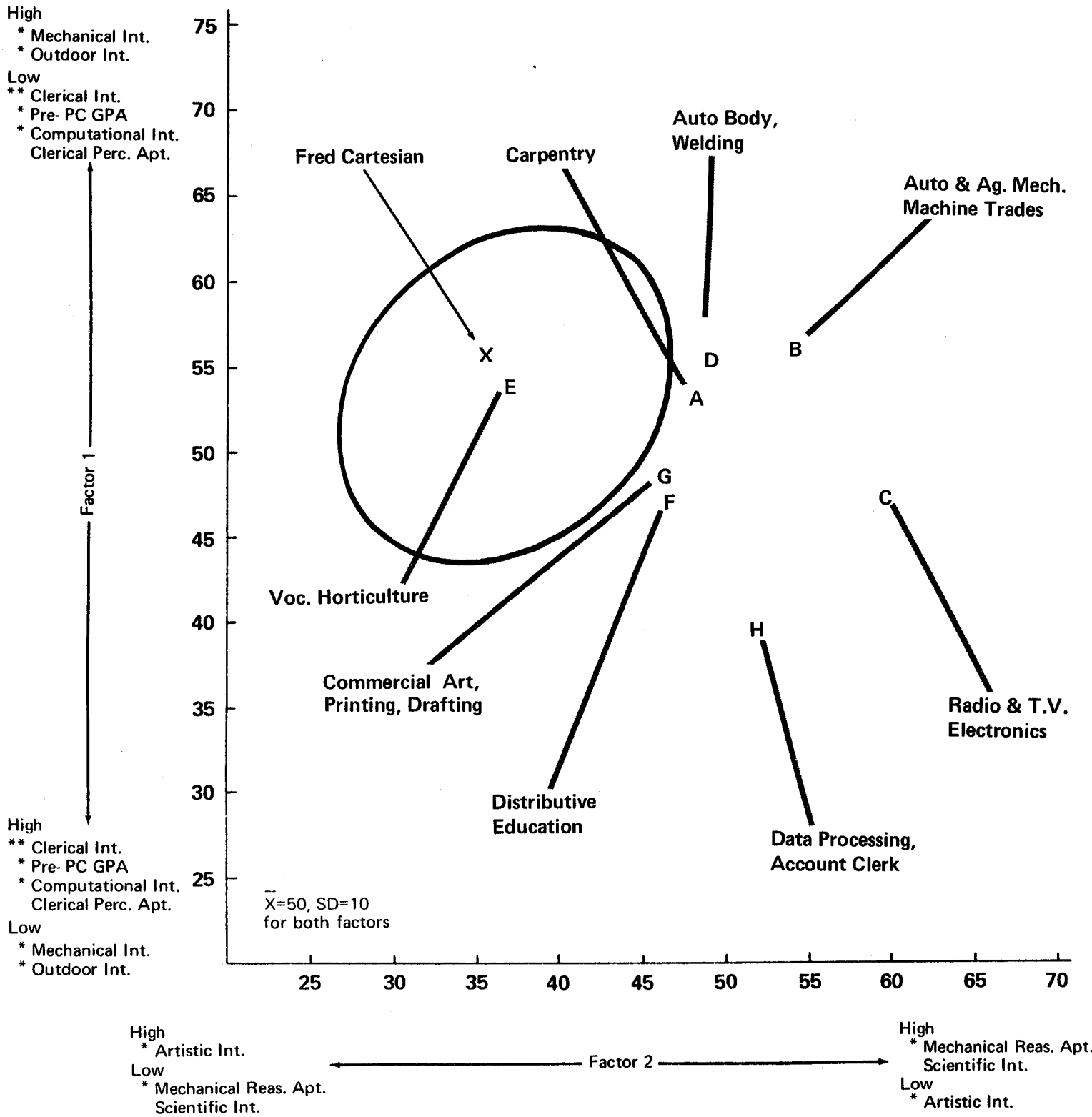

Fig. 1. Similarity Score Profile for Fred Cartesian.

differences among criterion groups, if present in the data, are presented in a manner that permits the counselee to "try the various groups on for size."

It should be noted that an extreme score on any one of the variables shown as factor anchors could, by itself, have a major influence on Fred's factor scores. Hence, Fred's test score reports should be consulted while discussing his similarity score profile. (Fred's counselor would probably want to do this anyway in order to facilitate Fred's participation in the test interpretation process.) The factor positions of the vocational programs, on the other hand, are unlikely to be subject to the influence of extreme scores on one or two variables. These positions are, after all, based on group means rather than the scores of a single individual. It is well-known that the spread of group means on a variable will be much less than the spread of individual scores.

Similarity and the Status Quo

Once the reasons underlying Fred's similarity scores have been determined, Fred and his counselor may be able to develop a program of activities and study that will increase his similarity score for a given criterion group. The feasibility of doing this would, of course, depend on the variables involved. However, the suggested strategy represents an example of a counseling application of test data that facilitates change in the status quo rather than merely a representation of it.

Another strategy can be used in combating the status quo, in this case, a strategy that reflects institutional goals. Suppose a college is unhappy with the characteristics of members of certain curricular groups. For example, its engineering students need more math, or its business students don't know how to spell. As French (1956) has noted, the similarity score technique, when used with unselected criterion groups, might result in encouraging students with similar deficiencies to enter these areas. Use of regression-based success estimates in conjunction with similarity scores would guard against this. In fact, Tatsuoka (1956) has developed an index which combines success and similarity estimates into one, overall probability. The index has considerable promise for placement applications. However, guidance applications appear limited because the joint index makes it impossible for a counselee to place separate values on the success and similarity estimates. Instead, he is confronted with a single number somewhat analogous to a joint index of height and weight.

Two additional procedures can be employed by the college to combat possible perpetuation of curricular group deficiencies through use of similarity scores. Both involve the strategy of redefining the criterion groups. The first, an empirical procedure, involves the selection of criterion group members according to predetermined definitions of satisfactoriness. Thus, engineering students with poor math backgrounds and business students who flunk the freshman English course could be eliminated from the criterion groups. The second, ad hoc procedure for redefining criterion groups involves the arbitrary assignment of group position on the test variables or discriminant factors that are thought to be important. For example, current engineering students could be assigned a much higher mean on a math proficiency exam than they actually have. Or, the position of the mechanics and machine trade group (area B) shown in Figure 1, might be moved to the right on Factor 2, thus requiring counselees to have a higher level of mechanical reasoning aptitude and scientific interest to appear similar. In each case, parallel adjustments could be made in the calculation of similarity scores. Further discussion of this strategy for combating the status quo has been provided by Rulon et al. (1967).

Some Technical Considerations

One obvious limitation of similarity score profiles is the difficulty in representing more than two tests or factor dimensions at one time. Discriminant analysis, fortunately, results in a reduction in the number of dimensions needed to represent criterion group differentiation. Usually two dimensions are sufficient. Nevertheless, the similarity score profile technique can be used with three factors by developing a series of profiles representing group positions on the first two factors for successive values of the third (Prediger, 1970). Instances in which more than three factors would be required to represent criterion group discrimination are rare, judging from the results of discriminant analyses reported in the literature.

So far, the discussion has involved only one or two general approaches which have been used to develop estimates of similarity to various groups. The similarity score approach illustrated above gives an *independent* estimate of a counselee's similarity to each of the criterion groups under consideration. The second approach, which is based on the maximum likelihood principle, provides probabilities that take into account the *relative* degree of a counselee's similarity to each of the criterion groups (Cooley & Lohnes, 1962). The resulting scores are given as decimal probabilities which total 1.00. Thus, if five criterion groups of equal size were involved and a counselee were equally similar to all five, his scores via the second approach would be .20 for each group. This would be true whether his similarity scores were all 99 or all 1. That is, relative degree of similarity rather than absolute amount is determined.

As another example, suppose that a counselee had factor scores of 70 and 25 on Factors 1 and 2, respectively, in Figure 1. Through use of the maximum likelihood approach, he would receive a very high score for area E, possibly even higher than Fred Cartesian's score. This would occur because the counselee's *relative* similarity to students in area E is much greater than his similarity to students in the other areas. However, his *actual* degree of similarity is quite low, as can be seen by plotting his factor scores on Figure 1. Since a counselor (and counselee) would undoubtedly want to know this, the educational-vocational counseling applications of the maximum likelihood approach are limited.

If, on the other hand, one is interested in allocating individuals to treatment groups so as to achieve some overall goal of efficiency or correct placement, the maximum likelihood procedure would be an appropriate technique to use. When differences in criterion group size and dispersion are taken into account, the predictions based on maximum likelihood procedures maximize the classification accuracy achievable by the predictor variables (Cooley & Lohnes, 1962).

Recapitulation

The following seven points have been emphasized in the foregoing discussion of objective techniques for data-information conversion:

1. Information from tests, when viewed in the context of decision theory, can play an important role in vocational development.

2. This role is primarily one of stimulating and facilitating exploratory behavior.

3. Two data-information conversion procedures—similarity scores and success estimates—are crucial to this role.

4. On the basis of both logical and technical considerations, similarity scores are more appropriate than success estimates in stimulating and facilitating exploratory behavior. Success estimates

represent an important consideration during the *process* of exploration.

5. Similarity scores eliminate much of the guesswork inherent in test profile interpretation.

6. Graphical procedures are available to provide help in understanding the reasons underlying a given counselee's similarity scores, thus avoiding the take-it-or-leave-it aspects of test interpretation based on similarity scores alone.

7. These procedures can also facilitate use of test data to initiate changes in counselee characteristics and/or the characteristics of groups representing various choice options, rather than merely to represent the status quo.

Implications

All of this is likely to be of little comfort to the conscientious counselor or personnel worker who has neither the time, training, nor inclination to become involved in data-related duties as versus people-related responsibilities. Few test users would argue about the need to strengthen the bridges between test scores and their meaning for the counselee; but how is the job to be done?

Two major stumbling blocks to data-information conversion and the prerequisite validity studies are data collection and analysis, fields in which great strides have been made in the last 10 years through the use of computers. In addition to providing help with record-keeping functions, computers have made time-consuming and/or highly sophisticated data analyses economically and psychologically feasible. Approaches to data-information conversion that have been available for some time are now possible on a large scale. This is nowhere better illustrated than in the work of Project TALENT staff members, in particular, Cooley and Lohnes (1968). However, practical applications of Project TALENT findings are limited because of the multitude of measures involved and their unavailability to practitioners. Unless the test equating studies proposed by Cooley and Lohnes (1968) eventually are undertaken, counseling use of Project TALENT data will be restricted to special programs such as Project PLAN (Flanagan, 1969).

The computer-based *system* illustrated by the Cooley-Lohnes studies is generalizable to other settings, however. Development of such systems, either by educational institutions or private enterprise, and provision for wide access to them are essential to any major improvements in test interpretation procedures. If systems for data-information conversion were readily available to the local practitioner, his only tasks would be to ask important questions of his data—and then help his counselees use the resulting information. Much of the work required in data preparation could be completed by clerical help or one of the several types of guidance technicians proposed by Hoyt (1970).

Data-information conversion systems will never replace professional knowledge, judgment, and experience. However, they can go a long way toward moving test interpretation beyond the era of squint and tell.

PART 2: FIELD TRIAL WITH FEEDBACK

As noted in Part 1 of this report, the vocational counselor who looks to empirical data for aid in test interpretation faces several problems. One of the most serious is the paucity of validity data supporting many uses of tests in vocational counseling. Equally serious, however, is the limited practical value of the validation studies available. As commonly reported, these studies provide the counselor with no direct help in bridging the gap between the test score and its meaning for the counselee. Indeed, the counseling *use* of information obtained from validation analyses is seldom reported in the literature. Test manuals do sometimes present experience tables, regression equations, or group profiles based on restricted samples. However, the counselor usually has only a set of norms, the suggestions in the test manual, and his own experience to guide him. Empirically based procedures for converting test data to readily usable counseling information, while available in theory, are largely lacking in practice. Such procedures will not remove all of the guesswork from test interpretation. However, they can place test interpretation on a more objective foundation.

Problem

The primary purpose of this study was to develop and demonstrate a system for converting test data to locally validated counseling information. Reactions of counselors and students to the use of this information in 12 field-test high schools are summarized. In the development of the computer-based data-information conversion system, heavy reliance was placed on the decision-oriented paradigm for local guidance research proposed by Clarke, Gelatt, and Levine (1965), and the multivariate descriptive strategies represented by the work of Cooley and Lohnes (1968, 1971). Longitudinal validation studies involving correlation and discriminant analyses were conducted to provide the empirical base needed for data-information conversion. Two conversion procedures were used: experience (expectancy) tables and similarity (centour) scores.

Although similarity score procedures were developed 20 years ago (Tiedeman, Bryan, & Rulon, 1951), their use in an ongoing guidance program is quite rare. In Figure 2, an illustration of similarity scores is presented in conjunction with the student report form used (with slight modifications) in counseling potential vocational education students in the field-test high schools. The similarity scores for Fred Cartesian, a fictitious counselee, appear on the "computer-printed label" to the right center of the form. As explained on the form, these scores reflect the similarity of Fred's aptitudes and interests to the aptitudes and interests of successful and satisfied students enrolled in eight vocational program areas.

Previous research has shown that the relationships between antecedent and outcome variables required for data-information conversion are likely to vary from one setting to another (Bennett, Seashore, & Wesman, 1966; Ghiselli, 1966; Passmore, 1968; Prediger, Waple, & Nusbaum, 1968). Hence, the nature of these relationships must be determined for the setting in which data-information conversion procedures are to be used. For this reason, answers to the following *research questions* were sought:

Similarity Score

1. Is it possible to differentiate successful and satisfied students enrolled in 12 vocational educational programs through use of aptitude and

EXPLORING PENTA-COUNTY VOCATIONAL PROGRAMS

If you are thinking about going to Penta-County, you probably face a difficult decision—the choice of which vocational program you wish to enter. This report won't tell you what to do. But it will provide some information that can help you explore what Penta-County has to offer. The vocational programs at Penta have been grouped into the 12 areas listed to the left of the box below. Your counselor will give you a label that fits over the box. This label contains scores giving a rough estimate of your *similarity* to students in the different programs. These "similarity scores" are based on aptitude and interest tests you have taken in the last year.

THE KEY POINT IS THIS: The higher your score for an area, the more *similar* you are to students in that vocational area. The highest score you can get is 100. The lowest score is zero. A zero score for area E would mean that your test scores do not look like the scores made by students in vocational horticulture. It's still O.K. to consider horticulture, however. Test results, after all, don't give the whole picture. You must consider them *along with all the other things* you know about yourself and Penta-County programs.

THE BEST WAY TO USE THIS REPORT is to find the vocational programs in which you score the highest. These are programs you might want to explore—find out more about. Perhaps you would not have thought of them otherwise. You certainly don't want to overlook a good possibility. There's too much at stake.

VOCATIONAL AREAS

Mostly boys enroll

√ A. Carpentry
B. Auto & Ag. Mechanics, Machine Trades
C. Radio & TV, Electronics
D. Auto Body, Welding

Both boys & girls enroll

√ E. Vocational Horticulture
F. Distributive Education
√ G. Commercial Art, Printing, Drafting
H. Data Processing, Account Clerk

Mostly girls enroll

I. Child Care Aide or Ass't., Community & Home Service, Dietary Aide
J. Cosmetology, Dental Assistant
K. Co-op Office Education, Office Machines
L. High Skill Steno

SAMPLE LABEL

032154 FRED E CARTESIAN 10/14/69

STUDENT SIMILARITY SCORES FOR P-C VOC. PROGRAMS

AREA=	A	B	C	D	E	F	G	H	I	J	K	L
SCORES=	41	14	03	26	87	25	28	01				
RANK=	2				1		3					
AREA=	A	B	C	D	E	F	G	H	I	J	K	L

PROFILE FACTOR SCORES: 56, 36

SO HOW DO YOU USE THE SCORES ON YOUR LABEL?

First, paste your label on the box shown above. Next, find and rank your top 3 or 4 scores. Give the highest score a rank of 1, etc., and write the ranks on the line below your scores. Finally, put a check mark beside the *names* of the 3 or 4 areas ranking the highest. These are the areas that your test results suggest you might want to find out more about. Some students receive low scores in all of the areas. This simply means that the test results aren't of much help in suggesting areas to explore. Whether your scores are "high" or "low," your counselor can help you figure out why they came out the way they did.

In order to judge *how successful* you might be in a program, you must also consider if you have the course work, aptitudes, and personal desire that is needed. This report does *not* tell you that. However, with the help of your counselor and your parents, you *can* use it along with other information as you explore the programs available at Penta-County.

Fig. 2. Similarity Score Report Form.

interest measures obtained prior to entry into programs? If so,

2. Which measures are most effective and what is the nature of the group differentiation that is achieved?

Experience Tables

3. Within each of the vocational program areas, considered separately, which of the aptitude measures has the highest correlation with success?

4. Is the use in vocational guidance of the best, two-variable combination of predictors warranted on the basis of the level of correlation achieved and the contribution made by each predictor?

Although the answers to the previously stated questions are specific to the setting in which the study was conducted, the techniques are directly transferable to other settings. For example, the same questions could be asked of data obtained from students prior to entry into various occupational groups or college majors.

Procedures

A detailed description of the research design and statistical analyses required to answer the four questions on antecedent-outcome variable relationships has been presented by Prediger (1970). Only a summary is given here.

Subjects and Variables

The subjects were enrolled at the Penta-County Vocational High School, an area vocational school serving 14 feeder high schools surrounding Toledo, Ohio. Students entering Penta-County as juniors or seniors in the fall of 1966, 1967, and 1968 formed the sample (N = 1,584) from which various analysis groups were identified. Although the same schools were involved, the analysis sample did not overlap with the field-test sample.

Scores from the following tests and inventories were used as antecedent variables: General Aptitude Test Battery, Mechanical Reasoning subtest of the Differential Aptitude Tests, and the Kuder Preference Record—Vocational. The 20 measures involved were generally obtained during the fall of the year preceding a student's entrance into the vocational school, although the actual time of testing was left to the discretion of feeder school counselors. Since several Kuder scales are subject to substantial sex differences, normalized standard scores based on separate percentile norms for males and females were used in the analyses.

Score reports for the above measures were provided to feeder school counselors for use in helping students explore the vocational programs available at Penta-County. The scores were not used by Penta-County personnel for placement of students in programs. Instead, students applied for the programs of their choice.

One additional antecedent variable, student GPA prior to entering Penta-County (PRE-GPA), was also available. Typically, PRE-GPA was based on all feeder school grades received during the freshman year and the first semester of the sophomore year.

Design

The 24 programs offered at the vocational school were grouped into the 12 areas listed at the left of Figure 2. Regression analyses required to answer Research Questions 3 and 4 were performed, separately, for each of the 12 areas. However, answers to Research Questions 1 and 2 required that discriminant analyses be conducted *across* the various areas. If the analyses were performed on all 12 areas simultaneously, sex differences from area to area might obscure other differences among program areas. One might find that the interest and aptitude measures chiefly differentiate programs enrolling girls from those enrolling boys, which would be of little value since there are better ways to differentiate girls from boys. Clearly, a design was needed that controlled for the effect of sex differences on differences among programs.

To minimize the problem noted previously and at the same time provide for comprehensive analyses, the 12 vocational areas were organized into the following groups: areas enrolling primarily males (N = 503), areas enrolling primarily females (N = 598), and areas having a substantial enrollment of both males and females (N = 483). As shown in Figure 2, the male, female, and mixed groups each included four areas. Separate discriminant analyses were run on the eight male and mixed groups combined (the M-MF analysis group) and the eight female and mixed groups combined (the F-MF analysis group). Similarity scores were also based on this grouping. Each analysis group had about 1,000 members, with the mixed group appearing in both analysis groups.

The vocational areas included in the discriminant analyses required by Research Questions 1 and 2 did not include students who (a) dropped out of school or returned to the feeder high school, (b) expressed dissatisfaction with program choice, or (c) failed to achieve a GPA of 1.8 (on a 4-point scale) in their *vocational* courses. In this sense, students in the discriminant analysis criterion groups can be described as "successful and satisfied."

The regression analyses required by Research Questions 3 and 4 excluded only those students who left school before they had established a grade record. Vocational course GPA at the time of graduation or dropout was used as the criterion of success. The median number of students in the 12 vocational areas involved in the regression analyses was about 110.

Results and Conclusions

Multivariate analyses of variance conducted on the aptitude and interest measures showed that both types of measures, used alone or in combination, differentiated the vocational areas far beyond the .01 level of significance. Thus, an affirmative answer was obtained for Research Question 1. Discriminant analyses were used to identify the dimensions (factors) of test data that best differentiated the areas. Since a large proportion of the discriminating power of the measures was concentrated in the first two factors, attention is focused on these two factors in the results following.

The nature of the factors that best differentiated the vocational areas in the M-MF analysis group and the manner in which these areas were differentiated can be seen from the "similarity score profile" presented as Figure 1 in Part 1 of this report. (A profile was also developed for the F-MF analysis group.) The axes of the coordinate grid, which are scaled with a mean of 50 and a standard deviation of 10 for the 8 vocational programs combined, represent the two most effective discriminant factors. The position of each vocational area mean (centroid) on the factors has been plotted as a single point, as have the factor scores of our fictitious counselee, Fred Cartesian. (These scores appear at the bottom of the label in Figure 2.) Perspective on amount of overlap among the areas is provided by the ellipse enclosing the scores of about 50% of the members of Group E, vocational horticulture.

Similarity score profiles provide a concise answer to Research Question 2. As noted in Part 1 of this report, aptitude and interest measures having a substantial relationship with the factors are shown as anchors on the horizontal and vertical axes. In Figure 1, the masculine-mechanical areas (auto body, welding, carpentry, auto mechanics, etc.) are all relatively close together and toward the mechanical-outdoor interest end of Factor 1. Vocational horticulture differs from these groups chiefly in its position toward the artistic interest end of Factor 2. The data processing and account clerk groups tend to be characterized by high clerical and computational interest, PRE-GPA, and clerical perception aptitude. The radio, TV, and electronics groups are not exceptional in these respects, but they do have relatively high mechan-

ical reasoning aptitude, scientific interests, and possibly low artistic interests. The positions of other areas can be analyzed in a similar fashion.

Correlation analyses using the aptitude measures as predictors and vocational area GPA as the criterion of success were run for each of the 12 areas. In answer to Research Question 3, the correlations showed that PRE-GPA was, without exception, the best predictor across the areas. Depending on vocational area, a variety of other measures ranked second in order of effectiveness. The correlations obtained with PRE-GPA ranged in size from .30 for carpentry to .70 for high skill stenography, with the median being about .45.

The most effective combination of two predictors was determined for each vocational program group by means of multiple correlation analyses. In answer to Research Question 4, practical application of two-variable predictor combinations was warranted in all but 2 (carpentry, and auto body and welding) of the 12 vocational areas. The multiple correlations ranged in size from .36 for carpentry to .73 for high skill stenography. The median was about .49. There was substantial variation among the aptitude measures accompanying PRE-GPA in the two-variable combinations. For example, mechanical reasoning was the second variable for the auto mechanics area, and finger dexterity for the cosmetology area. In general, very little predictive ability was lost by using the best combination of two predictors rather than the best three.

Cross-validation analyses based on fall of 1969 entrants will be conducted when these students have had a chance to graduate. A follow-up study has been completed for 1966 and 1967 entrants. This study, and the studies that are projected, will provide post-high school criteria of vocational development, satisfaction, and success.

Data-Information Conversion

The results described above provide the potential area vocational school student with little help in the exploration of vocational program choice. Practical payoff from the statistical analyses does not occur until the results are used to convert student data into counseling information.

In the case of success estimates, data-information conversion was readily accomplished via single-entry and double-entry experience tables. Single-entry experience tables showing the percentage of students obtaining various vocational program GPAs at various levels of PRE-GPA were developed for each of the 12 vocational areas. Double-entry tables based on the best combination of two predictors were developed for the 10 areas in which this was warranted. Through use of these tables, counselors and students could see the nature of the relationship between the most effective aptitude measures and vocational program success.

Similarity scores, the second data-information conversion procedure, were based on a combination of 10 of the most effective aptitude and interest measures. Separate sets of similarity scores were developed for boys and girls. Each set contained scores for the eight vocational program areas appropriate to the student's sex. Reports were in the form of a computer-printed label attached to a preprinted interpretation sheet similar to the one shown in Figure 2. Emphasis in the use of these reports was in stimulating students to explore those programs for which they received the highest scores. Counselors also received similarity score profiles for use in representing, visually, a student's similarities and analyzing their basis. This was accomplished by plotting the factor scores reported for each student on the appropriate similarity score profile, as illustrated for Fred Cartesian in Figure 1. Both the amount and direction of difference between a student's position and that of the various vocational areas provide information relevant to vocational counseling. A detailed description of this test interpretation procedure is provided in Part 1 of this report.

Field Tests

Initial field tests of the similarity score reports involved 160 potential vocational school enrollees attending four feeder high schools during the 1968-69 school year. Field-test counselors felt that the similarity scores were much more helpful than local norms or regular test score reports. However, they sometimes found that the similarity scores were difficult to interpret, especially when a student's scores were all low or when a student questioned why his scores came out as they did. As a result of these reactions, similarity score profiles (e.g., Figure 1) were developed to facilitate similarity score interpretation.

Field testing during the 1969-70 school year involved approximately 900 potential vocational school enrollees attending 12 of the 14 feeder high schools. In addition to the commercially available test score reports, counselors received similarity score reports, a set of experience tables, a set of similarity score profiles, and an interpretive manual. Suggestions for improvement resulting from the second field test chiefly involved modifications of the similarity score profiles to facilitate their introduction to students. The profiles initially provided to the counselors contained ellipses showing the distribution of students in each of the eight vocational areas appropriate to the student's sex. To reduce the visual confusion experienced by some students and counselors, two series (one for girls and one for boys) of three similarity score profiles were developed for field testing during the 1970-71 school year. Figure 1 represents the intermediate stage in the series for boys. The first profile in the series contained no ellipses while the third profile contained ellipses for all eight areas. Depending on student need and understanding, any or all of the three profiles can be used in test interpretation.

An informal survey of student reaction to reporting procedures was obtained after the 1969-70 field tests. Nine of the 12 schools identified a "reasonably representative" sample of students who had received the reports. When asked "Did you find the Similarity Scores . . . to be helpful as you thought about programs that you might enter at Penta-County?", only 13 of the 166 students in the survey chose the response option: "They really weren't of any help to me." Another key item on the student survey was worded as follows: "What was the *main way* in which Similarity Scores were helpful to you? (Please check only one response.)" Student response percentages are shown in parentheses after each of the following response options:

1. They weren't of any help. (8%)
2. They told me which program I should enter. (6%)
3. They suggested programs that I hadn't thought about before. As a result, I looked into some of these programs. (38%)
4. They backed up the program choices I had already made. (34%)
5. They suggested that some programs I had been thinking about might not be as "right" for me as some other programs. (13%)
6. They told me that I shouldn't go to Penta-County. (1%)

It is encouraging to note that few students viewed the similarity scores as telling them what to do and that most students saw the scores playing either an exploratory or a confirmatory role. Student comments on the reporting procedures were especially refreshing. Who could feel disappointed by a test interpretation that ". . . told a little more about me that I didn't quite know"!

Discussion

Vocational counseling has much to gain from the availability of validated test information. The data-information conversion procedures illustrated in this paper have been available for a number of years. Existing computer programs (Cooley & Lohnes, 1962, 1971) make them feasible for any counseling agency or guidance department having access to a computer of moderate size. Regional services analogous to test scoring services could also be established.

Local norms are now in widespread use when once they existed mostly as illustrations in textbooks. Perhaps locally validated test information will also become commonplace.

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