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ABSTRACT

The present study devised a computerized assignment-by-preference algorithm for a ninth-grade exploratory curriculum. The problem addressed was one of maximally mapping all students into 8 of 12 vocational programs in terms of their preferences for studying each of the programs and the assignment restrictions established by the school. To minimize the errors of misplacement and produce a successful algorithm for the problem faced, it was found that a procedure had to be devised which both individually-referenced and group-referenced students' program preferences into one meaningful statistic. In general terms, this problem was one of combining bipolar data so that every plus-minus combination produced a unique scale point. The values of this latter scale made it possible to determine which students should be assigned to what programs under the criteria specified. Once all students were assigned to programs, this same scaling procedure was used to develop a sequence statistic which allowed programs to be maximally ordered for those students most likely to be affected by this variable. Twelve percent of the student body (N=440) expressed dissatisfaction with the program assignments they received. Interviews, however, revealed that most of these students misunderstood the restrictions governing assignments. (Author)

SCALING PREFERENCE DATA FOR PROGRAM ASSIGNMENTS

James Carifio, Boston University

The present study devised an assignment-by-preference algorithm for a ninth-grade exploratory vocational curriculum. This curriculum offered 12 different five-week programs, 8 of which the student had to explore during the course of the 40-week school year. These 12 programs were grouped into 4 basic categories (3 of the 12 in each), and a student's assignments to programs were restricted in that he had to explore at least one program in each of the 4 basic categories devised by the school during the course of the year. Therefore, although the problem was assigning a student to the 8 programs he is most interested in pursuing, 4 of these 8 programs had to meet the "one from each of the basic areas" requirement. In addition to the basic parameters just defined, the school requested that once 8 programs had been assigned to a student, these programs were to be optimally sequenced for that student in terms of his pre-entry achievement and affective profile. Lastly, there was also a restriction that no more than 40 or less than 36 students be in any one program during any 5-week cycle.

It was found that to minimize the errors of misplacement and produce a successful algorithm for the problem outlined above, a procedure had to be devised which both individually-referenced and group-referenced students' program preferences into one meaningful statistic. In general terms, this problem was one of combining bipolar data so that every plus-minus combination produced a unique scale point. The values of this latter scale made it possible to determine which students should be assigned to what programs under the criteria specified. Once all students were assigned to programs, this same scaling procedure was used to develop a sequence statistic which allowed programs to be maximally ordered for those students most likely to be affected by this variable.

Data were collected from 440 students in the present study. Both raw and scaled preference scores proved to be approximately interval and linear. Twelve percent of the population expressed dissatisfaction with the program assignments they were given by the algorithm used. Interviews, however, revealed that most of these students were displeased because they misunderstood the nature of the problem. Some of these students thought that they only had to study those programs they wished to study (i.e., 2 or 3 for the year), while others were unaware of the basic requirements restrictions. Once the problem was understood by these students, their assignments seemed to make sense to them. This source of invalidity, however, must be attended to more closely in future used of the algorithm.

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It may be argued that one of the major criteria for assigning a student to a given vocational program should be that student's interest in or preference for the program, particularly if the program is <u>exploratory</u> in nature. A large number of studies have shown that high school and/or college interest is the best predictor of long-term vocational choice (see Berdie, 1960; Kahout and Rothney, 1964; and Campbell, 1965). Other studies, however, have shown that approximately 80% of the population switches careers within five years of graduation (Gross, 1967; Flanagan et al., 1971). Since career switching in the latter studies was found to be relatively independent of aptitude and post-training levels of achievement, the "interest-determination-of-choice" stage of the vocational development process would seem to be occurring in the marketplace rather than in the classroom.[1] The implementation of an assignment-by-preference policy, therefore, might not only transfer elements of this process back to the classroom where vocational theorists tell us this selective-adaptive stage of development to a large degree belongs (Super, 1960; Tiedeman and O'Hara, 1963; Crites, 1968; and Holland, 1970), but it might also help to maximize the impact that schools and guidance services have on the career development and decision-making process.

In reality, an assignment-by-preference policy would not be as unbounded as it might appear to be, particularly at the exploratory program level. As

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[1] Approaching this issue from another direction, Greenberg and Greenberg (1974) found that approximately 80% of the population in business and industrial settings were either misemployed or underemployed. As misemployment and underemployment were found to be independent of aptitude and post-training levels of achievement in this study, these researchers interpreted their findings as being an indication of the small role interests or abilities play in the assignment of people to jobs or training programs in these settings.

discovery learning proved to be less effective than guided discovery learning (Wittrock and Wiley, 1970), so one would expect guided exploration to be more conducive to vocational development than unfettered exploration. Students, therefore, would most likely be required to study at least one program from basic groupings of programs during their first year of training, so that some type of balanced exploration would be achieved. From this vantage point, those programs the student was still interested in would be pursued in greater depth, and there would be an option for exploring new programs as alternatives to those which proved to be unsatisfactory career paths. Over the years, students would become highly trained in one or more areas via this selective-adaptive process, and minimally trained in others as they progressively re-examined, differentiated, and narrowed their choice of programs. The guided exploration concept, therefore, not only facilitates the development of skills in related vocational areas, but it also facilitates a flexibility in career paths for students due to the acquisition of basic prior training in several different vocational areas.

To the best of this writer's knowledge, preference is not actually used as the major criterion for assigning students to exploratory programs in any systematic or meaningful way. The purpose of the present study, then, was to work out such an assignment procedure for a ninth grade exploratory program, and it is this procedure as well as the results that it produced that will be reported in this paper.

The Problem

The present study was conducted at a regional vocational-technical high school in eastern Massachusetts.[1] The ninth grade curriculum of this school offered 12 different five-week programs, 8 of which the student had to explore during the course of the forty week school year.[2] These twelve programs were grouped into 4 basic categories (see Figure 1), and a student had to explore at least one program from each of the four basic categories during the course of the year. Therefore, although the problem was one of assigning a student to the 8 programs he most preferred, 4 of these 8 programs

Category I	Category II	Category III	Category IV
Culinary Arts	Commercial Arts	Electronics	Building Trades
Health Services	Graphics	Instrumentation	Metal Fabrication
Horticulture	Distributive Education	Power Mechanics	Machine

Figure 1: Basic Categories from which Students must Explore at least one Program.

had to satisfy this "one from each of the basic categories" requirement. In addition to the parameters just defined, the school further requested that once 8 programs had been assigned to a student, these 8 programs were then to be optimally sequenced for that student in terms of his pre-entry achievement and affective profile. Lastly, there was also a restriction that no more than 40 students be in any one program during any given five-week period, and that some type of flexibility be built into the solution for special-needs students. The

[1] This writer would like to thank the Minuteman Regional Vocational-Technical High School for their cooperation and support of this research. He would also like to thank Superintendant Samuel S. Sains for his continual encouragement in this project and for his commitment to implement educational innovation.

[2] All programs were offered on a repeating basis (every five weeks) over the course of the school year.

curriculum just described is prototypical of ninth-grade exploratory programs, as are the set of restrictions under which an assignment-by-preference algorithm must be derived.

Discussion of the Problem

Given the problem and restrictions outlined above, the construction of a workable assignment-by-preference algorithm seemed to be dependent upon several factors. The first of these factors was the supply-demand problem. Only 67% of the student population could be assigned to a given program over the course of the year. Conversely, only 33% could avoid assignment. Obviously then, the degree of fit any algorithm could produce under such conditions would be dependent upon the nature of the population to be assigned and the flexibility of the restraining parameters.[1] Given that the school employed in the present study had a semi-open admissions policy where 80% of the student population was admitted by random selection, preference distributions could be expected to be highly skewed, since there was no "control at the door" of this variable. An equitable procedure for dealing with this supply-demand problem, therefore, had to be devised if a solution to the problem was to be obtained.

The second factor a workable assignment-by-preference algorithm seemed to be dependent upon was the way in which student preferences were measured. There is a large amount of literature concerning the differences between

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[1] The degree of fit produced by any algorithm, therefore, can be expected to vary from group to group and situation to situation. It should be noted, however, that if the algorithm employed produces the best fit in terms of the restraining parameters, then one cannot improve upon the solution the algorithm provides without altering the nature of the restraining parameters.

directly expressed interests and inventoried interests (see Super, 1957; Super and Crites, 1962; and Campbell, 1965). Inventoried interests in the form of the Strong or the Kuder survey were originally considered to be the more valid and generalizable of the two modes, but more recent studies have shown that directly expressed interests have equal if not better predictive validity (Cooley, 1966; Holland and Lutz, 1967; Dolliver, 1969; and Flanagan et al., 1971). Correlations between the two modes have always ranged from moderate to high (Whitney, 1969), but reflection on the issue should lead one to conclude that inventoried interests such as the Kuder or the Strong survey would not be very useful for assigning students to programs by preference, since one would be confronted with the problem of mapping generalized inventory scores (or profiles) to specific programs in a valid way. This mapping task would not only be difficult to do, but also highly errorful given the range of correlations that are continually observed between the variables involved. This writer, therefore, chose to use expressed preferences as the mode of measurement in the present study. This decision, however, only resolved the problem of what was to be measured.

The question of how expressed preferences should be measured is somewhat more complicated than the issue discussed above. Preference is most typically measured by some type of forced comparison (ranking) technique (Guilford, 1954; Edwards, 1956; Torgeson, 1958; Bock and Jones, 1968). These procedures range from very simple to quite complex techniques with the power (quality and usefulness) of the resulting data being a function of the sophistication of the technique. Complex comparative techniques are most commonly used in measuring preferences because the data obtained by these techniques can be intervalized and an equal unit scale constructed for the stimuli. As will be pointed out in greater detail later in this paper, ranking procedures will not produce a good solution to the assignment-by-preference problem because they do not allow the relative degree of program preferences to be expressed by students in a way that makes it possible to say that student A prefers program X more than student B does, given the fact that both students prefer program X over program Y. Such statements are not only essential to the solution of the problem but almost mandatory since it is non-differentiation (ties in preferences) that mitigate most against correct (non-errorful) assignments of students to programs.[1] Given this point, a categorical measuring procedure was therefore chosen for use in the present study which allowed students to directly express their degree of preference for assignment to each program. Whether or not this procedure produces interval data (which it came vary close to doing naturally) is completely irrelevant to the assignment-by-preference algorithm devised, since it is only the rank order of the queues for programs that is important to the solution.[2] More will be said on this point later, but it is interesting to note that the most recent

[1] At the more mundane level, one must also remember that one is attempting to assign ninth-grade students to eight of twelve programs, and that paired or multiple rank comparisons would not only tend to be excessive in this situation, but they would also most probably tend to lack face validity with such young and eager students. Simpler ranking procedures, of course, would be almost totally incapable of even approximating the poor solution to the problem that paired or multiple rank ordering techniques would provide.

[2] The intervality of the raw data would be an important issue if the mechanics of the scaling procedures to be reported in this paper were to be used in other types of situations such as scoring dependent variables in experimentation. As the data to be scaled by the procedures to be reported in this paper can be intervalized beforehand (see Edwards, 1956, or Torgeson, 1958), this point is no problem, since this first-order scaling may be applied before the second-order scaling is carried out.

attempts to measure vocational interests have also chosen to employ some type of categorical procedure (see Flanagan and Cooley, 1966; and Madaus and O'Hara, 1968).

The third and most crucial factor a workable assignment-by-preference algorithm seemed to be dependent upon was the development of a new kind of scaling procedure. This scaling procedure had to index student preferences so that the psychological dimensions inherent in these preferences were expressed and the logical properties needed for making the right assignment decisions about each student were also obtained. What needed to be scaled, then, were students and not stimuli or categories.[1] Although the procedure arrived upon was more a product of logic-in-use than anything else, it is somewhat reminiscent of Coombs' unfolding technique (Coombs, 1964). The procedure is substantially different from Coombs' technique, however, in that it disregards the scaling of stimuli and categories as being of any real importance and concentrates on the scaling of students for decision-making purposes. Aside from producing a way to meaningfully index bipolar data, this writer feels that there is heuristic value in the procedure devised, since it began with the requirements of the problem and then proceeded to construct the statistic needed for a solution rather than the other way around.

Given that the relative degree of student program preferences can be obtained and meaningfully scaled, two more components were needed for a solution to the problem initially posed in this paper beside the actual assignment algorithm itself. The first of these components was a series of computer

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[1] Data transformation or indexing technique might be a more appropriate name for the procedure devised by this writer, but the question seems to be moot since the technique not only draws upon the literature of scaling, but also attempts to cope with the same kind of problem in a different way.

programs which will scale the data obtained and then actually carry out the assignment process according to the flexible algorithm devised.[1] A flexible algorithm is needed because various options have to be open for use due to the degree-of-fit factor discussed earlier. These options will be discussed more fully in the body of this paper, but they essentially boil down to a set of procedures for obtaining the best fit for the data at hand, given extreme skewing and inequitable demands for programs within basic categories.

The school at which the present study was conducted, it will be recalled, requested that programs be optimally sequenced for students in terms of their entering achievement and affective profiles. The last component needed for a solution, then, was a procedure for effecting this request.[2] An analysis of the sequencing specifications provided by the school revealed that ideal program patterns could be worked out for only a fixed number of students. An index, therefore, which indicated the order in which students should be scheduled had to be constructed to achieve an optimizing solution. The requirements of this index, it turned out, were identical to those of the assignment index described earlier. The same scaling

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1 These programs have been developed and are available in standard FORTRAN compatible with the IBM 360/170. Readers interested in further information about these programs should contact this writer at Boston University's Educational Research Laboratory. This writer would like to thank Mr. Norman Goldman of Compunetics for writing the last four programs in this series since this project could not have been completed without his expert and timely help.

2 The reader will note that this component is not part of or required for a workable assignment-by-preference algorithm. It is the last component needed to solve the problem as posed by the school at which the present study was conducted.

procedure, therefore, was also applicable to this problem. It was realized, however, that a point would be reached where students could be (or would have to be) sequenced into the remaining tracks available, and provisions for this loss in degrees of freedom were built into the computer program written. It is from the vantage point of this discussion, then, that the details of the assignment-by-preference algorithm devised may be presented.

The Solution

The mechanics of the assignment-by-preference algorithm devised in the present study hinge first on measurement and then on composite-score scale construction. As previously mentioned, preference is most typically measured by some type of ranking procedure. Ranking procedures, however, do not allow one to know whether a student is relatively positive or negative towards any or all of the objects in the set being considered. Ranking procedures also do not allow one to know the relative degree of a student's preference for any one object in a set in terms of his preferences for other objects in the set. Both of these factors are important psychological considerations which need to be taken into account in assigning a student to one program as opposed to another. Therefore, a procedure which allows <u>the relative degree of preferences for programs</u> to be expressed by each student is essential for a solution to the assignment-by-preference problem. Such a preference score was obtained on each program from each student in the present study by a "stem-and-scale" set-up like the example given in Figure 2.

Horticulture

Ninth-grade students who choose the five-week introductory Horticulture program will grow a wide variety of plants, such as: flowers, fruits, vegetables, and ornamental plants. Instruction will be given in floral design, landscape design, and merchandising plant materials. Students will be taught safe use of tools, equipment and chemicals in commerical horticulture and commerical gardening. Learning experiences will occur in the greenhouse, retail florist shop, and on the school grounds.

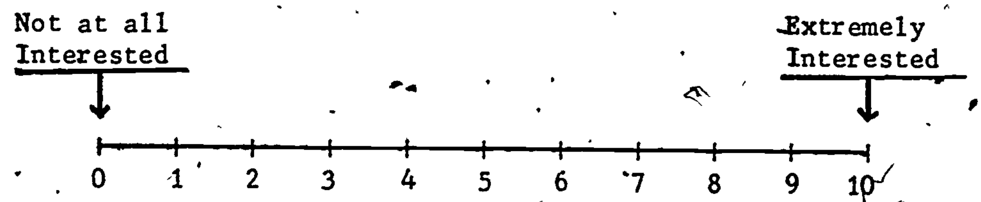

Figure 2: Example of Categorical Procedure Used to Measure Students' Preferences for Programs.

As can be seen from Figure 2, the stem of the set-up used in the present study was a paragraph which described what a particular vocational program would be like during the ninth-grade year. The scale was a zero-to-ten point anchored rating continuum located beneath the paragraph. A student expressed his degree of preference for studying the program described in the paragraph by making a slash (/) on the scale in the appropriate place.[1] As the zero-to-ten point scale beneath each paragraph was a hundred millimeter line,

[1] Twelve such paragraphs and scales were presented sequentially to each student in the same order in a booklet.

preference scores of 52, 96, 21, 8 and so on were obtainable for each student on each program by this procedure.[1]

Extensive prior training was given to students in the use of the rating scale shown in Figure 2. This training consisted of 110 attitudinal and self-concept items which employed the scale shown in Figure 2 as the mode of response.[2] Training was given in a testing session that occurred at least one week prior to the collection of the preference data itself.[3] An orientation program was also built into this first testing session which told students about each of the programs they could pursue, and students were urged to discuss their choice of programs with their parents prior to the next testing session.[4] Preference data was then collected at the next testing session, and a retest on this data was conducted for a subsample of 50 people at varying intervals.

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[1] Some minor modifications (additional scale anchors and a grouping together of programs that form a category) have been made to the set up just described in this year's implementation of the procedure. See the conclusion section of this paper for further details.

[2] This amount of training was completely fortuitous and is, of course, not requisite for use of this scale. Some practice with this scale prior to its use in gathering program preference data is recommended, however, so that students will be thoroughly familiar with the procedure at that time.

[3] Data were gathered on a number of variables from 440 students in 12 different towns according to variable collection schedules in the present study. Collection occurred over a five week period (May to June, 1974) and students participated in 3 testing sessions which were at least one week apart.

[4] To aid students and parents in this process, a flyer was passed out at the end of the first testing session, which contained the exact paragraph descriptions of programs that would be seen at the time the preference data was collected. The purpose of this flyer was to provide a medium of interaction that would elicit any specific questions students or parents had about ninth grade programs. An additional purpose was to ensure that students were familiar with the program descriptions.

Obviously, the nature of the data obtained by the categorical measuring procedure outlined above is the outstanding question at this point. Table I presents the reliability coefficients for the program preference data collected in the present study. As can be seen from Table I, the test-retest reliability coefficients ranged from + .86 to + .93 with the median coefficient being + .89.[1] Although these test-retest coefficients are somewhat inflated due to sample size, they are high enough to allow instability of preferences to be ruled out as a potential problem.

An intraclass correlation coefficient was also computed on the test-retest data obtained in the present study to see if the order of students' preferences for programs remained stable over time. As can be seen from Table I, the intraclass coefficient was observed to be +.91. Again taking sample size into account, the value of this coefficient is high enough to allow instability in the order of student program preferences to be ruled out as a possible problem with either the measurement procedure employed in the present study, or the assignment algorithm devised.

A Chronbach Alpha coefficient was computed for the entire sample employed in the present study to see if the program preference data collected was internally consistent. As can be seen from Table I, the Alpha coefficient was observed to be +.85. Given the number of items and the size of the sample, the value of this coefficient was high enough to conclude that systematic patterns of choice were present in the data.[2] Further analyses were therefore

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[1] Pearson product moment correlations were computed as the data proved to be sufficiently interval and linear.

[2] Systematic choices patterns are not a required characteristic of the data for the assignment algorithm devised.

Table I

Reliability Coefficients for Program Preference Data

Program	Time 1			Time 2*		r_{tt}**
	n	X	s	X	s	
Culinary Arts	50	61.4	31.6	62.1	30.5	.92
Health Services	50	44.6	34.6	46.8	33.4	.90
Horticulture	50	51.1	35.3	49.7	36.1	.86
Commercial Arts	50	45.6	31.5	44.2	33.7	.86
Distributive Education	50	65.0	28.5	66.1	27.2	.91
Graphics	50	55.3	29.9	53.9	31.8	.88
Electronics	50	65.0	31.1	66.7	33.7	.87
Instrumentation	50	49.8	31.0	47.1	32.3	.87
Power Mechanics	50	72.0	30.3	73.4	29.4	.91
Building Trades	50	75.8	27.7	77.1	26.2	.94
Metals Fabrication	50	72.7	29.1	74.3	27.6	.90
Machine	50	67.3	30.1	66.7	31.3	.88

median .89

Coefficient Alpha (time 1) = .85 (N=440)

Intraclass Correlation Coefficient (time 1/ time 2) = .91 (N=50)

* at least one-week interval between testings

** Pearson Product Moment Coefficients

done to clarify the nature of these systematic choice patterns.[1] These analyses revealed that traditional sex-role stereotyping was the most dominant factor in the determination of preference profiles. This finding is not only consistent with the literature in this area (Bailyn,1957; Clark, 1967; and Seigal, 1973), but supportive of several decisions made at various points in the assignment algorithm devised.

Figure 3 presents a plot of male and female preference profiles. Table II presents the correlation matrix associated with Figure 3, and Table III presents the overall distributions of preferences for programs. As can be seen from Table II, preferences for programs were moderately to highly correlated with each other. As can be seen from Figure 3, sex was the variable that would most account for the patterns of correlation coefficients that are given in Table II. Table III in relationship to Table II provides a great deal of evidence to support many of the arguments previously made, but the point to be noted at this time is that program preferences were as skewed and as variable as they were expected to be. Further information on the validity of the preference measure used in the present study will be given later in this paper.

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[1] The full details of these analyses are reported in the results section of this paper.

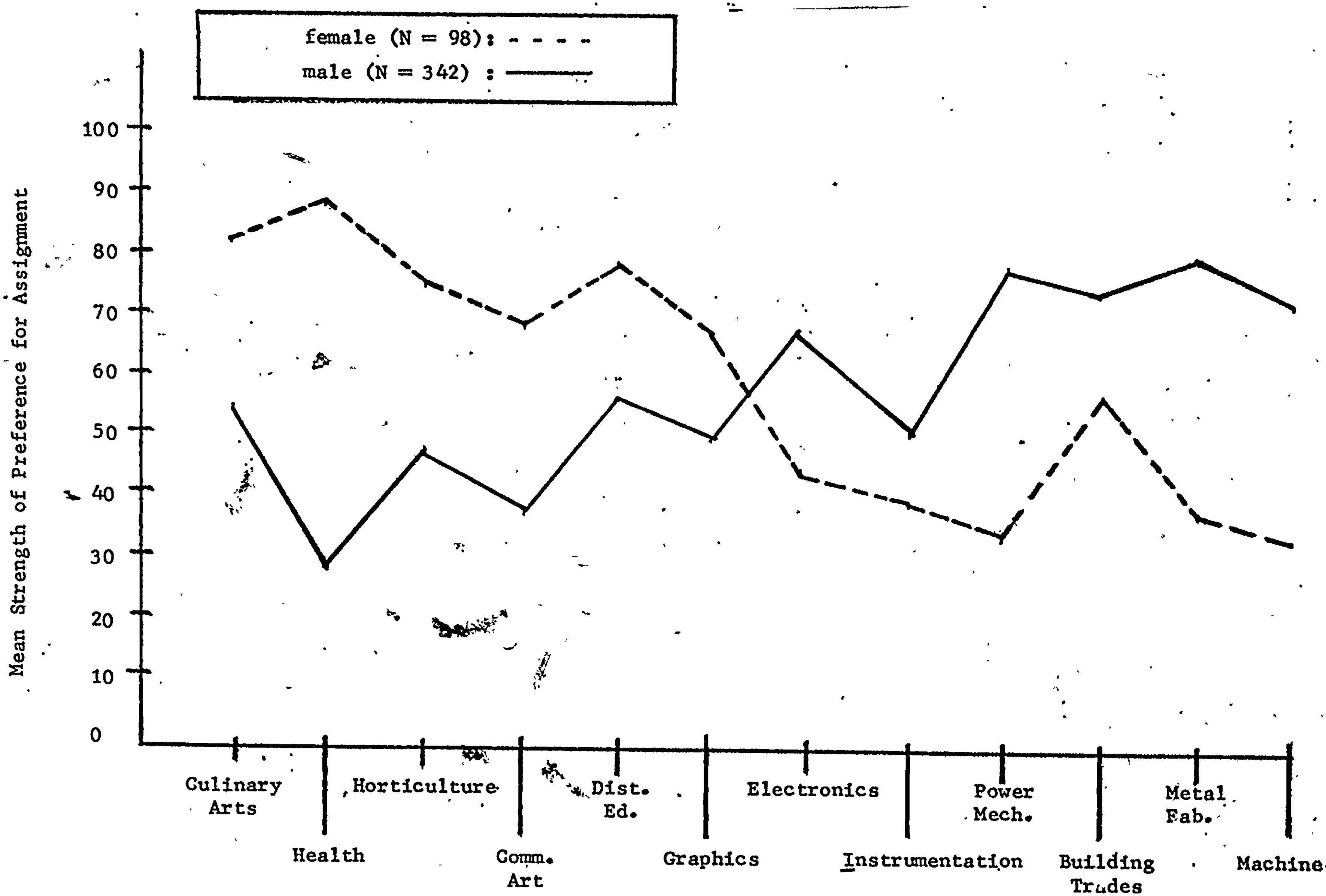

Figure 3: Plot of Program Preference Profiles for Male and Female Students' Programs.

Table II

Preferences and Sex Intercorrelation Matrix

	CA	HS	HO	CO	DE	GR	EL	IN	PM	BT	MF	M
Sex	37	65	42	42	29	20	-45	-08	-64	-38	-62	-51
CA		46	43	28	40	18	-14	00	-19	01	-15	-10
HS			40	39	37	21	-24	04	-40	-17	-35	-26
HO				30	28	20	-13	04	-16	02	-14	-06
CO					30	39	-15	12	-20	-08	-16	-13
DE						22	01	17	-08	06	-10	-03
GR							18	25	03	08	12	09
EL								44	54	35	58	45
IN									26	19	23	26
PM										41	68	59
BT											44	42
MF												67
M												

CA = Culinary Arts
HS = Health Services
HO = Horticulture
CO = Commercial Arts
DE = Distributive Education
GR = Graphics
EL = Electronics
IN = Instrumentation
PM = PM Mechanics
BT = Building Trades
MF = Metals Fabrication
M = Machine

The reader should note that the sex variable was scored 1 for males and 2 for females in the present study, thus explaining the direction of the correlations observed.

Table III

Distributions of Program Preferences

Programs	N	Mean*	Median	St. Dev.	Skewness	Kurtosis
Culinary Arts	440	61.39	63.74	31.659	-0.488	-0.927
Health Serivces	440	44.63	42.11	34.611	0.164	-1.295
Horticulture	440	51.06	45.01	35.303	-0.075	-1.173
Commercial Arts	440	45.60	46.11	31.462	0.139	-1.073
Distributive Education	440	64.99	68.92	28.549	-0.580	-0.614
Graphics	440	55.32	55.12	29.857	-0.317	-0.885
Electronics	440	65.00	71.17	31.077	-0.626	-0.745
Instrumentation	440	49.76	55.39	31.020	-0.060	-1.073
Power Mechanics	440	71.98	76.01	30.262	-0.983	-0.100
Building Trades	440	75.77	81.46	27.692	-1.234	0.623
Metals Fabrication	440	72.71	77.42	29.124	-1.038	0.040
Machine	440	67.33	75.86	30.128	-0.772	-0.446

* Scores on all distributions were observed to range from zero to one hundred.

The degree to which the categorical measuring procedure used in the present study succeeded in obtaining interval data was tested by the method of successive intervals (Edwards, 1956; Bock and Jones, 1968).[1] Using the upper-limit cumulative frequencies for the ten categories involved, the appropriate P, Z, and W matrices were generated for the total sample as well as for males and females separately. These W matrices were then column-averaged to produce the empirical estimates of category widths. These estimates are

Table IV

Empirical Estimates of Category Widths

	Categories							
	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8
Males (N = 342)	.27	.20	.25	.24	.26	.21	.26	.26
Females (N = 98)	.20	.16	.19	.24	.31	.23	.30	.33
Total (N = 440)	.24	.20	.21	.23	.25	.20	.23	.30
	Cumulative Values							
Males	.27	.47	.72	.96	1.22	1.43	1.69	2.04
Females	.20	.37	.56	.80	1.11	1.34	1.64	1.97
Total	.24	.43	.64	.87	1.12	1.32	1.55	1.85

[1] As previously mentioned, the intervalness of the data obtained is only important in terms of other uses of the scaling procedure outlined in this paper. As far as the assignment algorithm devised is concerned, the scaling procedure needs only to achieve the correct rank order of students for programs.

presented in Table IV. As can be seen from Table IV, the category values for the total sample are approximately equal-unit widths with the exception of the last category given in the table.[1] Although females seem to contribute more to the variability in overall category widths than males, this result is due more to sample size and normalcy violations than anything else.[2] Therefore, as the raw preference scores collected in this study so closely approximated equal-unit data, they were not intervalized in the present instance, although this most certainly could be done given the need or predilection.

The degree to which the categorical measuring procedure used in the present study succeeded in obtaining linear data was tested by the graphic application of the Normit Chi-square procedure (Bock and Jones, 1968). Observed cumulative percentages were plotted on normal probability paper using the empirically determined category widths as the boundary values. A best-fit line was then drawn in and expected percentages estimated from this line. These estimated percentages were then used along with the observed percentages to compute goodness-of-fit Chi-squares by the procedure outlined in Bock and Jones (1968). Table V presents these Chi-squares for the total sample as well as for males and females separately. As can be seen from Table V, the male data conforms well to a linear model with the female and total sample

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[1] The widths of categories 8-9 and 9-10 cannot be estimated as the 9-10 category is unbounded (p equally infinitely). It should also be noted that the size of the intervals given in Table III is arbitrary and may be multiplied by a constant if so desired.

[2] Since the method of successive intervals assumes a normalcy of preference distributions in the generation of the Z matrix, the variability in category widths observed in Table IV are to a degree the product of the averaging of the transformed z-values across the categories of skewed distributions.

Table V

Chi-squares for Goodness of Linear Fit

Program	Males (N=342)	Females (N=98)	Total (N=440)	df
Culinary Arts	1.22	4.5	3.08	2
Health Services	4.25	8.12	6.45	2
Horticulture	4.22	5.91	14.72*	2
Commercial Arts	10.61*	7.2	18.76*	2
Distributive Education	10.45*	15.57*	12.90*	2
Graphics	6.67	24.37*	7.15	2
Electronics	7.34	9.69*	3.68	2
Instrumentation	11.1*	6.57	5.61	2
Power Mechanics	7.58	6.45	9.74*	2
Building Trades	21.7*	2.33	10.53*	2
Metals Fabrication	4.77	3.14	3.30	2
Machine	3.5	10.31*	8.36*	2
TOTAL	93.41	104.16*	104.58*	66

* $p > .01$, the recommended significance level for this test.

data being only slightly deviant.[1] However, as the Normit procedure is extremely conservative and somewhat sensitive to skewing, it is suggested by Bock and Jones (1968) that the observed deviations should be quite large before they are considered to be truly significant. Therefore, it would seem that the program preference data collected in the present study is sufficiently linear to rule this factor out as a problem.[2] Consequently, no type of linearization was performed on this preference data before scaling it.

Given the evidence that has been presented, it would seem warranted to conclude that the categorical measuring procedure used in the present study succeeded in obtaining suitable data. Tables IV and V show that the data obtained was approximately interval and linear. Table I shows that the data obtained was highly reliable and internally consistent. A close examination of Tables II and III will show that the arguments that were made in advocating the use of a categorical measuring procedure are supported. In group terms, the distances between program means in Table III are not equal. Given the size of the correlations in Table II, the standard deviations given in Table III are large enough to support the contention that substantial preference differences do exist between students who have the same rank orderings of programs.[3] Again, the magnitude of the group means given in Table III indicates that students are not as negatively disposed towards the middle ranked

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[1] The actual plots of the data showed that observed departures from linearity tended to occur as a result of discontinuity in the uppermost or lowermost categories of the scale.

[2] In order to double check this point, the Normit Chi-squares were recalculated by the procedures previously described using equal-unit estimates as category boundaries since this was the type of scale that students actually responded to when expressing their preferences. In all except three instances, non-significant Chi-squares were obtained.

[3] A detailed checking of the data obviously confirmed this fact.

programs as one might be lead to believe in the absence of relative estimates of preference. Given these findings then, the question of meaningfully indexing this preference data can be addressed with the knowledge that the foundations upon which it rests are sound.

As previously stated, scaling student preferences so that correct program assignments could be made was the central and most difficult problem encountered in the present study. Although explainable in a number of different ways, the nature of this problem and the logic used in solving it can best be understood by considering what various raw preference scores could mean for students.

Suppose a student had a raw preference score of 40 for some program.[1] A raw preference score of 40 may not be as low as it might appear to be in terms of this student's expressed desire for the program. If this student's preferences for all other programs were below 40, for example, then his preference for the "40 score" program would be extremely high relative to his other choices. If this were indeed the case, then this student would most desire assignment to the "40 score" program, since this is the program for which he has the greatest expressed affinity.

Obviously, the converse of the above point could be true for a student who had a preference score of 80 for some program. A raw preference score of 80 could be the lowest score in this student's string of scores. If this were indeed the case, then one could say that this student would be less disposed to accept an assignment to this "80 score" program than to other programs, since this "80 score" program is his least desired preference.

A T-scaling of each student's preference scores in terms of his <u>own</u>

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[1]The reader will recall that students rated each of 12 programs on a zero to one hundred scale.

mean and standard deviation will eliminate the relativity problem just described.[2] This conversion will express each student's preference scores in terms of his own relative affinities for assignment; i.e., those programs the student is most disposed towards will have scores greater than 50, and those he is least disposed towards will have scores of less than 50.[2] Individually T-scaling program preference scores, however, only solves one dimension of the relativity problem being faced.

Although a student might be positively disposed towards a particular program, the strength of his disposition might not be as great as another student's. This comparative factor is the second type of relativity problem that is operational in the preference scores collected, even if they are individually T-scaled. If one accepts the assumption that the student with the stronger preference should be assigned to the program first (given that someone will eventually have to be closed out of the program due to the limits set), then one must find a way of dealing with this second relativity problem which does not compromise the solution that has been obtained for the first. Although several alternative procedures most likely exist, the one developed by the present writer is given below.

If one took all the preferences for a particular program and T-scaled them using the mean and standard deviation of the group, then each student's T-score would express the strength of his desire to be assigned to that program relative to the desires of other students in the group. This second

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[1] A T-scale has a mean of 50 and a standard deviation of 10. Since a T-scaling is only a transformation of the data, both the order and distance between preference scores is maintained.

[2] Although large differences were found between the means and standard deviations of individuals, no significant differences were found between the means and standard deviations of males and females as a group. This result was a prime factor in the rejection of the sex difference hypothesis earlier.

group-normed T-scaling of raw preference scores would create the following logic table in relationship to the individually-referenced T-scores previously obtained.

		Individual's Preference for Program in Relationship to his Other Preferences.	
		− (< 50)	+ (> 50)
Strength of Individual's Preference for Program as Compared with Other Student's Preference for the Program.	− (< 50)	- / -	+ / -
	+ (> 50)	- / +	+ / +

<u>signs given individual by group</u>

What becomes obvious from the table given above is that using either T-score by itself (group or individually-referenced) to make program assignments will lead one to exclude students from programs that one does not want to exclude. For example, if a student's preference for a program was high (+) in terms of his other preferences, but low (-) in terms of the group's desire for the program, one would not want to exclude this person from the program in favor of someone who was high in terms of group preference, but low in terms of individual preference. What becomes evident, then, is that a procedure is needed for combining a student's group and individually-referenced T-scores into one index that expresses the correct rank order of assigning students to a particular program so that the errors of misplacement can be minimized. This needed procedure is the new scaling method referred to at the beginning of this paper. From this method, one obtains 12 indexed scores for each student which reflect the logic of the table given above, and these indexed scores are the values used to assign each student to his 8 programs by the algorithm devised. With this scaling procedure, one has all that is needed for a solution to the assignment-by-preference problem, since the scores that it produces gives one the information one needs to make the correct assignment decision for any person or any program in terms of the governing criteria. Given then that the basic logic underlying the assignment-by-preference solution has been brought to a clear enough conclusion, the details of this scaling method can now be presented.

Any attempt to combine bipolar data must contend with the problem that basic arithmetic operations do not produce logically unique scale points.[1] For example, a student who is slightly negative towards a program in terms of the group's desire for admission to the program, but highly positive towards the program in terms of his own preferences for assignment should not end up having a combined score that is the same as a student who has the opposite characteristics. The present writer, therefore, developed an equation which produces unique and proportional scale scores for each +/- and -/+ combination. These latter combinations are, of course, the crux of the problem, since -/- and +/+ combinations posed no difficulty. The equations for all four of the bipolar combinations in the logic table previously presented are given below:[2]

(1) General form for the <u>positive-positive</u> category:

$$X_s = LBC_1 + (T_{gr} - \bar{T}_{gr}) + (T_{ir} - \bar{T}_{ir})$$

where:

X_s = resulting scaled score

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[1] This point is true for both signed and unsigned data.

[2] The reader will note that the equations given are set up like a computer program;i.e., they assume that the values of the student's two T-scores are known, thus allowing the correct scaling equation to be chosen based on the logic category the two scores represent.

LBC_1 = the lower bound constant of the category; in the present case 600

T_{gr} = Group-referenced T-score for the person for this program.

$\bar{T}_{gr}$ = 50, the mean of the T-scale

T_{ir} = Individually-referenced T-score for this person for this program

$\bar{T}_{ir}$ = 50, the mean of a T-scale

(2) General form for the positive-negative category:

$$X_s = LBC_2 + \frac{B_1[(\bar{T}_{gr} - T_{gr}) + B_2(T_{ir}^2 + T_{ir})]}{B_3}$$

where:

LBC_2 = the lower bound constant; in the present case 500

B_1 = category scaling constant; in the present case 1000

B_2 = the within factor scaling constant; in the present case 15

B_3 = category scaling constant; in the present case .67

(3) General form for the negative-positive category:

$$X_s = LBC_3 + \frac{B_1[(\bar{T}_{ir} - T_{ir}) + B_2(T_{gr}^2 + T_{gr})]}{B_3}$$

where:

LBC_3 = the lower bound constant of the category; in the present case, 400

(4) General form of the negative-negative category:

$$X_s = UBC_4 - (\bar{T}_{gr} - T_{gr}) - (\bar{T}_{ir} - T_{ir})$$

where:

UBC_4 = the upper bound constant of the category; in the present case; 400

Application of the above equations will produce scaled preference scores for each student for each program which are in the following form:

A score from:

300-400: indicates a preference which is negative in terms of the student's desire for assignment to the program (individual reference), and negative in terms of a student's desire for the program relative to other students' desires for the program (-/-). The lower the score, the more negative the student is. Obviously, these are the last students you would assign to this program.

400-500: indicates a student who is negatively disposed towards the program in terms of his other choices, but positively disposed towards the program as compared with other students (-/+). These students would be second last to be assigned to this program.

500-600: indicates a student who is positive towards assignment to this program in terms of his other preferences, but low in terms of his position in the group of people who would like to get into this program (+/-). These students would be the second group of people assigned to this program.

600-700: indicates a student who is positive towards assignment to this program in terms of his other preferences, and high in terms of the group desire to get into the program (+/+). These students would get assignment to this program first.

In terms of the original logical table given, this scale may be expressed as:

Individually T-scaled Scores

		— (< 50)	+ (> 50)	
Group T-scaled Scores	— (< 50)	— / — 300-400	+ / — 500-600	<u>signs given individual by group</u>
	+ (> 50)	— / + 400-500	+ / + 600-700	

Score values on the scale just presented clearly indicate the degree of student satisfaction that will be obtained by a particular program assignment. Values on this scale also indicate a student's assignment priority in terms of both group and individual demands for a program. Therefore, since satisfaction and decision-making are both psychological constructs, the scaling procedure described in the present study has been named the IGP scoring technique by this writer (Individually-referenced, Group-referenced, Psychological composite).[1] This scoring technique obviously has applications to other problems involving the use of bipolar data.[2] Further, as the IGP technique vector indexes the values of a given logic table, the output from one table may be used as the input to another. An example of this double-indexing strategy is the sequencing statistic developed in the present study.

Extensive computer simulations were run on the scaling equations presented in this paper to check them out through all possible combinations of raw score values from zero to one hundred.[3] In all cases, unique scale points were produced. Figure 4 presents a representative sample of these simulated values for equation (2); i.e., the positive-negative category. As can be seen from Figure

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[1] Whether or not one agrees that raw preference scores are psychologically scaled by the procedure outlined in this paper is of little real importance. The point of importance is that the IGP scoring technique provides a procedure for equitably resolving the issue of who should gain admission to a particular program. This issue, after all, was the crux of the problem given the assignment requirements and restrictions previously outlined.

[2] Meaningfully indexing factor scores or demonstrating various kinds of changes are but two example that come to mind.

[3] Although T-scores almost always range from 20 to 80, these values were the logical limits of the equations presented. The reader should note, however, that if T-scores greater than 80 are observed or expected to occur in the data, the category boundries in the equations given should be made at least 200 points apart to ensure unique scale points and scores acroos all of the people in the sample. As preference distributions were negatively skewed in the present study, this point posed no problem, nor should it in most instances.

Positive Value	Negative Value	Scaled Value
50.0	0.0	638.300
50.0	5.0	638.295
50.0	10.0	638.290
50.0	20.0	638.280
50.0	30.0	638.270
50.0	35.0	638.265
50.0	40.0	638.260
50.0	49.9	638.250
50.5	0.0	639.061
50.5	20.0	639.041
50.5	30.0	639.031
50.5	40.0	639.021
50.5	45.0	639.016
50.5	49.9	639.011
51.0	0.0	639.830
51.0	30.0	639.800
51.0	40.0	639.790
51.0	49.9	639.780
60.0	0.0	654.950
60.0	49.9	654.900
80.0	0.0	697.250
80.0	49.9	697.200

Figure 4: Representative values from equation (2); the positive-negative category of the fourfold IGP logic table.

4, the rank order of the positive dimension of this category is maintained across the resulting scale values, and logically negative raw scores cause discriminations to be made only between students who have the same positive dimension scores. The way in which negative dimension scores cause dsicriminations to be make in equation (2) is simply the result of a decision made by this writer based upon the psychological considerations involved in the problem.[2] This decision, of course, could be reversed given the need or the predilection.

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[1]Among other things, this writer did not want a student wo tended to use the lower parts of the scale to be squeezed out of a program by a student who tended to use the upper parts of the scale.

Using the preference data collected in the present study, resulting scaled scores were also tested for intervality and linearity by the procedures outlined before. When the square roots of the polynomials in equations (2) and (3) were used, the resulting scale values were found to be approximately interval and linear within the normal boundries of a T-scale (i.e., values 20 to 80).[1] Beyond these findings, several other points should perhaps be noted in passing. First, the equations given are only one of many sets of equations that could be used to solve the bipolar scaling problem, and a far more elegant set most likely exists. The second point that should be noted is that the solution to the plus-minus combination problem comes from the weighted polynomial in equations (2) and (3), and the weighting constant of 15 seems to be a necessary value. The last point that should be noted is that the equations given work empirically, and this, if nothing else justifies their usage. Given this fact, then, the assignment-by-preference algorithm devised may be presented.

The Assignment Algorithm

Once 12 IGP scores have been obtained for each student, the assignment process is ready to begin. The first step in this process is a T-scaling of each student's IGP scores within the basic categories that comprise the "one from each" requirement. This T-scaling makes the four highest scores in each student's string his four most preferred programs in terms of the "one from each" requirement.[2] Using

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[1] Equations (2) and (3) were left in their polynomial form in generating the scaled scores used in the present study for tie-breaking purposes. Left this way, these two equations will produce non-linear scores in the extreme ranges of their respective categories.

[2] An extra 10 point is added to each student's highest within-category T-score to ensure that no errors are made due to extreme or narrow within categories variations. The reader will also note that this T-scaling makes every student's number one choice a "requirement," and that for some students, it could make their top four choices "requirements."

these T-scores, students are now assigned to their four highest choices. Given that only 1760 program assignments are being made to 3800 available openings, it is highly unlikely that any student will not get his top four choices in this round.[1]

The next step in the assignment process uses a student's <u>original</u> string of IGP scores to assign him to his four remaining programs with those programs he has already been assigned to zeroed out.[2] Starting with the most popular program, students are now assigned to those opening available beginning with the highest 600 score available and working backwards until either the programs limit or a score below 500 is reached. If a score below 500 is encountered before the program's limit is reached, the algorithm simply stops and goes on to the next program until the round of all programs is complete. This stopping at a score of 500 allows students to gain as many positive programs as possible across all available openings, and, at the same time, to have 8 program assignments before the next round begins.

The next round in the assignment process focuses on those students who do not have 8 program assignments and those programs which are under-subscribed. Starting with the least under-subscribed program, students are now assigned to the openings

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1 If any closing out does occur from a particular program, the algorithm simply goes back to the original IGP scores for the subgroup of students in question, and assigns those students with the highest IGP scores to the available openings. The remainder of the students wanting the program are then given their next highest choice within the category and so on until the basic requirements round is completed.

2 Besides eliminating students from consideration on programs to which they have already been assigned, the placement of zeroes in their strings of IGP scores also allows a lot of book-keeping to be done. How many openings are available in a particular program can be quickly determined from a count of zeroes. How many program assignments a student has on any given pass may also be determined in the same way because every time a student receives a new assignment, the new program is also zeroed out in his string. Once a student has 8 zeroes in his string, he is, of course, eliminated from the process altogether.

available beginning with the highest 400 score and working backwards until either the program's quota or a score below 400 is reached. If a score below 400 is encountered before the program's quota is reached, the algorithm once again stops and goes on to the next program. Hopefully, most students have 8 program assignments by the time this third pass on programs is complete.[1]

Students who do not have 8 program assignments at this point have scores in the 300 category for all of the under-subscribed programs remaining. A minimization of the degree of negativity present in each under-subscribed program, then, would be the goal of this round. Therefore, starting again with the least under-subscribed programs students with scores in the 300 category are now assigned to the opening remaining beginning the the highest 300 score and working backwards until the program's quota is reached. Once this round of under-subscribed programs is complete, all students will have 8 program assignments.

Obviously, the degree-of-fit obtained by the algorithm just described is the outstanding question at this point. Table VI presents the distributions of initial demands for programs that were observed in the present study arranged by IGP score categories. As can be seen from Table VI, "male" programs exceeded their limits (295 students maximum) in the positive categories, while "female" programs were extremely under-subscribed and had a great number of students in the negative-negative category. The number of -/+ and +/- students who might have been wrongly

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1. If all students were assigned to 8 programs at this point, the algorithm would of course stop.

2. In situations where there are equitable distributions of choices for programs, there should only be a few students needing only one or two programs in this round. The conditions that tend to produce a large number of students needing 2 or 3 assignments in this round are students who have 3 or 4 extremely high program choices and no difference in preference on the rest, or students who are extremely negative towards more than 4 programs.

Table VI

Distributions of Initial Demands for Programs

	(-/-) 300-400	(+/-) 400-500	(-/+) 500-600	(+/+) 600-700	Limit
Culinary Arts*	181	16	20	223	295
Health Services	235	61	1	143	295
Horticulture	226	27	11	176	295
Commercial Arts	226	84	0	130	295
Distributive Education	165	15	25	235	295
Graphics	197	47	16	180	295
Electronics	161	16	22	241	295
Instrumentation	194	98	1	147	295
Power Mechanics	122	1	55	262	295
Building Trades	87	3	66	284	295
Metals Fabrication	111	2	57	270	295
Machine	137	9	28	266	295

*Programs arranged in terms of the four basic categories that comprise the "one from each" requirement for all students.

assigned if raw scores alone were used can also be easily observed from Table VI. Fitting students to programs with demand distributions like those given in Table VI would be a difficult task under any set of restrictions, let alone those that were operational in the present study. If nothing else, at least the nature of the decisions one is making is clarified by the scaling procedure developed for use in the present study.

Table VII presents the results of the "basic requirements" round in the algorithm previously presented. As can be seen from Table VII, no student failed to

Table VII

Program Assignments on the "Basic Requirements" Round

	(-/-) 300-400	(+/-) 400-500	(-/+) 500-600	(+/+) 600-700	Total
Culinary Arts*	33	4	13	106	156
Health Services	32	15	1	98	146
Horticulture	28	10	5	95	138
Commercial Arts	27	18	0	86	131
Distributive Education	13	3	13	144	173
Graphics	22	6	8	100	136
Electronics	18	2	9	131	160
Instrumentation	21	15	0	86	122
Power Mechanics	6	0	30	122	158
Building Trades	10	0	26	107	143
Metals Fabrication	8	0	14	89	122
Machine	21	2	2	161	198

*Programs arranged in terms of the four basic categories that comprise the "one from each" requirement for all students.

receive his top four required choices. The reader should also note, however, that required assignments act to consume places in certain programs. This consumption of places by required assignments will prevent some students who are positive towards the most popular program from gaining access to them. This outcome, unfortunately, is unavoidable given the "one from each" restriction.

Table VIII presents the final results achieved by the assignment algorithm previously devised. If Table VIII is read in conjunction with Table VI (initial demands distributions), one can see that no +/+ student was excluded from any program. A large percentage of -/+ students did not receive assignments to four of

Table VIII

Distributions of Final Porgram Assignments for Students.

	(-/-) 300-400	(+/-) 400-500	(-/+) 500-600	(+/+) 600-700	Total
Culinary Arts	36	16	20	223	295
Health Services	90	61	1	143	295
Horticulture	87	11	21	176	295
Commercial Arts	81	84	0	130	295
Distributive Education	20	15	25	235	295
Graphics	52	47	16	180	295
Electronics	18	14	22	241	295
Instrumentation	49	98	1	147	295
Power Mechanics	6	0	27	262	295
Building Trades	10	0	26	259	295
Metal Fabrications	8	0	17	270	295
Machine	21	2	6	266	295

the programs they desired, but this result is due in part to the basic requirements restriction and the high demand for these programs. The number of -/- students that were actually assigned to programs, however, is exceedingly small in comparison to the expected rate of 145 students per program. Further, this expected value is only exceeded in two instances if one includes the +/- students in the count as well. Given that the scaling procedure developed in the present study highlights negative values whereas ranking methods disguise them, one would have to say from the results presented in Table VIII that more than a reasonable degree-of-fit was achieved by the algorithm devised. Further comment on this point, however, will be held in abeyance until after the program sequencing material has been presented.

Sequencing Program Assignments

Once all students have been assigned to 8 programs, other data is used to determine how these program assignments will be sequenced for each student.[1] The first factor that affected a student's sequence of programs was his status in terms of minimum academic skills that were required for certain vocational programs (Electronics, Instrumentation and Power Mechanics). If a student did not have the minimum skills needed for one of these programs, and he was assigned to that program, the program was to be placed in the last half of the school year for the student so that requisite skill-building time was gained.[2] Comparable criterion-referenced data was therefore collected on students as the first-step in a solution to this sequencing problem. The science, language and "abilities" data collected was then T-scaled and summed to form the first dimension of a four fold logic table.[3] The math data collected was then T-scaled and used as the second dimension of the logic table.[4] This logic table was then scored by the scaling procedure previously outlined to produce an IGP skills score for each student. This skills score was then used as the first dimension of the next logic table.

The second dimension that entered into the sequencing question was the

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[1] Obviously, if the requisite data is unavailable, programs are just randomly sequenced at this point and the process stops.

[2] If the student was assigned to all three of the programs mentioned, all three would be put in the last half of the year for him.

[3] Summed scores were divided by the number of variables involved to keep the resultant mean at 50.

[4] Poor math skills kept a student out of all programs whereas the other variables were deemed by the school to be only of secondary importance.

affective disposition of the student. If a student was highly alienated from school, this student was to be given his most preferred programs first, except if he did not have the minimum skills needed to succeed in these programs. Alienation from school data was therefore collected with Heussenstaam's scale and this data was T-scaled to form the second dimension of a new logic table with the IGP skills scores. This second order table was then scored by the scaling procedure previously outlined to give the sequencing index needed for a solution. Using this index, student program sequences were then constructed beginning with those students lowest on the scale (most difficult to obtain the correct order for), and working forward until all degrees of freedom were lost. After this point, the remaining students were fitted into the available patterns left.

Although all students were now assigned and sequenced, various hand adjustments had to be made at this point for the special-needs students in the school's population. School officials felt that some of the program assignments these students had were unsafe. Therefore, these special needs students were removed from the programs in question, and placed a second time in their most preferred programs. Students with 500-600 preference scores were placed into these vacancies if a "closed-out" had occurred, and if the student's "one from each of the four categories" requirement was not violated. Otherwise, vacancies were left unfilled.

It is interesting to note at this point that even under an assignment-by-preference model, there are compromises and a need for decision-making criteria which equitably resolve conflicting desires. Not all students who really want a program can be assigned to that program in all instances, due to the restraints of the physical resources available, state laws, and the philosophical requirements of broad exploration. Additionally, not all students who detest a particular program can be kept out of that program in every instance. The realities of having to bring some programs up to subscription in order to keep them running and deal with the "close-outs" from other programs impinges. Further, not all students can be handled under the general algorithm devised; i.e., students with special needs, however defined, must be dealt with on an individual basis by a human decision-making mechanism. In spite of these limitations, however, it is remarkable how well the ideal situations can be approximated by the algorithm devised.

Methodology

Data on 36 variables were collected from 440 students in three different testing sessions over a five-week period. Testing schedules were different for various groups of students as the data was collected at town sites (12 in all). As previously mentioned, criterion-referenced math, science, English and reading data were collected from students in addition to the program preference data obtained. The number of observations in the latter instruments ranged from 25 to 75 multiple choice items per test. Random samples of items were drawn from the non-verbal reasoning, verbal reasoning, spatial relations, and mechanical reasoning subtests of the DAT, and administered to students. The size of these random samples were 33% of the DAT subtest being sampled. Data from Heussenstraam's alienation from school scale was also collected, as was other data for school planning purposes.[1]

Results

Several results have already beenpresented in this paper, but it would seem pertinent to examine a few more before drawing any conclusions. Table IX

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[1] The reader desiring fuller details of the instruments, procedures and methodology used in the present study should contact this writer.

presents the factor structure of raw preference scores, sex, and other selected variables.[1] As can be seen from Table IX, the data matrix analyzed seems to reduce into male, achievement, female, and bisexual factors.[2] The independence observed between achievement variables and program preferences in Table IX is consonant with other findings (Tiedeman and O'Hara, 1963; Maduas and O'Hara, 1968), and indicative of the fantasy stage of vocational development. The relationship between sex and preferences for programs that may be observed in Table IX has already been discussed. This traditional sex-role stereotyping of choices (Factors I and III) is also well documented (Siegal, 1973). What is interesting to note in Table IX, however, is that a subsample of males and females seem to be present in this group of ninth-grade students who do not seem to conform to the traditional sex-role stereotyping pattern. Further investigations are presently being conducted on this subsample of students to see if some light can be shed on this result.

Another result that may be seen from Table IX is that students do not organize these 12 vocational programs into the same number or kind of categories that the school does. Other analyses revealed that females tended to have only three categories whereas males tended to have five. Overall then, one could say that Table IX provides strong evidence for the validity of the categorical measuring procedure used in the present study.

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[1] Principal-component, unity in the diagonals, eigen cut-off value of 1.00 analyses were performed throughout.

[2] The reader should note that the sex variable was score 1 for males and score 2 for females.

Table IX

Factor Structure of Raw Preference Scores and Selected Variables

Variable	I	II	III	IV	h^2
Sex	65	02	48	21	70
Mechanical Reasoning	-23	65	-17	-03	50
Verbal Reasoning	-06	65	14	-13	45
Non-Verbal Reasoning	-06	75	00	07	57
Spatial Relations	00	65	-20	17	49
Math Achievement	-09	78	06	08	63
Science Achievement	-08	79	08	01	63
English Achievement	23	58	19	-07	43
Reading Achievement	02	80	11	01	66
School Alienation	-01	12	-02	-43	20
Culinary Arts	05	00	80	-04	65
Health Services	37	00	66	24	63
Horticulture	06	04	69	07	50
Commercial Arts	23	07	38	55	51
Distributive Education	-02	13	63	21	45
Graphics	-08	12	23	70	56
Electronics	-68	08	-15	32	61
Instrumentation	-35	13	01	57	47
Power Mechanics	-81	-02	-15	01	70
Building Trades	-66	17	17	-08	50
Metal Fabrications	-83	00	-13	07	72
Machine	-78	05	03	04	62
Contributions	17.3	18.8	11.9	7.4	55

Table X

Factor Structure of Scaled Preference Scores and Selected Variables

Variable	I	II	III	IV	V	h^2
Sex	83	00	12	12	-07	72
Mechanical Reasoning	-26	-65	-12	00	08	51
Verbal Reasoning	02	-66	02	-14	-03	46
Non-verbal Reasoning	-03	-74	00	12	07	57
Spatial Relations	-12	-62	-04	35	15	54
Math Achievement	00	-80	-06	00	-07	64
Science Achievement	00	-80	01	00	-02	64
English Achievement	33	-58	00	-08	03	45
Reading Achievement	08	-81	05	05	-06	67
School Alienation	-03	-08	04	-10	90	83
Culinary Arts	51	00	42	-21	03	48
Health Services	74	04	14	00	-04	56
Horticulture	50	01	35	08	05	38
Commercial Arts	51	01	05	48	02	50
Distributive Education	45	-16	-03	-31	-24	39
Graphics	15	-09	-08	73	-13	58
Electronics	-50	-02	-46	-24	-16	55
Instrumentation	01	-07	-85	02	02	74
Power Mechanics	-75	03	-11	-17	00	61
Building Trades	-56	-15	26	-07	-25	48
Metals Fabrication	-80	-05	01	-05	07	65
Machine	-71	-04	11	-07	03	52
Contributions	21.4	18.8	6.4	5.5	4.7	58

Table X presents the factor structure of scaled preference scores, sex, and other selected variables. As can be seen from table X, the scaling technique employed in the present study acts to accentuate and clarify the findings presented in Table IX and discussed above. This demonstrated property, therefore, may be one of this scaling technique's advantages as a scoring procedure.

The last result to be presented obviously concerns the goodness-of-fit achieved by the assignment algorithm devised. Satisfaction-with-assignments data was not directly solicited from students.[1] Rather, complaints about program assignments were kept track of by the school's Student Program Co-ordinators, and a simple ratio developed.[2] In all 12% of the student population registered complaints about one or more program assignments. Interviews with complaining students, however, revealed that they were making complaints based on inaccurate information. Many complaining students thought that they only had to study as many programs as they wanted to in their first year at the school. Other complaining students were completely unaware of the "one from each of the basic categories" requirement, and thought they could study any 8 programs they wanted. Once the various requirements were understood by these complaining students, however, their assignments seemed to make sense to them. A re-analysis of preference scores revealed that about 28% of the students in the sample had only 2 or 3 true program choices (the rest being zeroes), or no program choices in one or more basic categories (the entire category being zeroes).[3] Aside from being a source of invalidity in the present data, this result is the factor that brought about the changes in the preference data collection format and orientation program mentioned earlier. Given this confusion, however, it would seem that the assignment algorithm devised succeeded in obtaining a good-fit for the data collected.

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[1] It was decided that this procedure might be too reactive, and, due to other sensitive school issues, set off some undesirable events.

[2] Student Program Co-ordinators are similar to guidance counselors, and work closely with students on a daily basis in the school.

[3] Another source of complaint from students was that they received only 2 out the 3 possible assignments to be had from a particular category. This outcome may in part have been due to the aberrations in the data just described.

Conclusions

It would seem that three conclusions could be drawn from the present study. First, the scaling procedure developed for use with bipolar data in this study provides a technique for making such data both meaningful and useful. This procedure would seem to have applications to many other situations. The second conclusion to be drawn from this study would seem to be that regardless of the program assignment model used, there are compromises that need to be made, and there is a need for explicit decision-making criteria which equitably resolve the conflicting goals operational in the situation. Given a clear specification of the problem and explicit decision making criteria, however, it would seem that the present study does demonstrate that solutions may be developed which effect desired education policy, such as the assignment-by-preference algorithm that has been outlined in this paper.

The third conclusion that could be drawn from this study is that measurement, psychology, and computer science have much to offer schools in effecting their philosophical, programmatic, and operational desires when they are viewed in a different perspective; i.e., as problem-solving technologies. Further efforts, therefore, would seem to be in order along these lines.

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