PRECISE MEASURES OF COGNITIVE STRUCTURES: PERCEPTION OF OCCUPATION NAMES

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Abstract

The model of occupational choice presented here is derived from a theory of self-concept in which individuals may place themselves relatively close or far apart from elements of that conceptual domain (such as occupational names), and so define themselves in relation to that domain. In this respect the model is considered to have utility in defining the individual in other conceptual frameworks. That individuals use a number of cognitive dimensions to inform their decisions about occupations complicates the study of this process. It is possible, however, to get valid and reliable representations of the occupations domain without a prior knowledge of these dimensions. Both University of Hawaii and Michigan State University students completed the same scaling instrument in which they were asked to determine the distances between all possible pairs of 15 occupations. The resulting space was found to be highly reliable (comparing two separate samples over a one year period in Michigan) and valid (the first two dimensions on which occupations are arrayed were described very well by known estimates of occupational prestige and the actual percentages of females in each of the occupations considered). The utility of the space was considered in terms of predicting occupational choice, counseling for employment, and understanding definitions of self.

The occupational structure of any society constitutes one of the most important substructures of the overall social structure, and the flow of persons from new generations to replace persons from older generations exercises a profound effect on the stability or change of the occupational and hence social structure of the society. Over the years the process by which young people enter the occupational structure has been increasingly well understood, and, although differences exist, some consensus seems to have emerged about a general model of occupational choice.

This general model assumes that the individual is born into a specific location in an already existing social structure (Blau & Duncan, 1967). This location constrains the range of alternative occupations available to the individual, the set of persons available to serve as "significant others," and the expectations those significant others hold for him or her (Woelfel & Haller, 1971). In turn, these expectations influence the individual's perceptions of both the occupational structure and of self (Woelfel & Haller, 1971; Saltiel, 1978). The relations that individuals see among themselves and within the set of occupations are finally thought to exert important influences over the actual occupational choices. This is subject, of course, to the constraints of available employment (Sewell, 1971).

This basic model has beem employed numerous times in an attempt to further explicate the processes by which parental statuses are transmitted across generations (Alexander et al., 1975; Otto and Haller, 1979). While the resultant research has focused exclusively on the processes by which persons aspire to and eventually attain different levels on the socioeconomic ladder, Woelfel (1975) has proposed a specific operational scheme for applying this model to explain and predict specific occupational choices. This scheme has recently been tested (Saltiel, 1978) with excellent results. It is the intent of this paper to show that the measurement system underlying this approach is valid, reliable, and easy to administer.

The theory behind this model rests on a social psychology, drawn primarily from Mead (1934), Fotte (1951) and other cognitive social psychologists, which emphasizes the behavioral implications of a "fit" between self-perception and occupational perception. Thus, following Lemert (1951), if a person perceives an act to be a criminal act, and perceives him/herself to be a criminal, then the likelihood of performing the act is higher than would be the cause if the act and the self did not "go together" or fit. Similarly, if a person defined him/herself as the type of person who should hold a high status job, the likelihood that he/she might choose job X would be higher than would be the case if perceptions of self and job did not match (Holland, 1966).

This type of theory places a high premium on the ability of the investigator to determine the basis of a person's classification not only of self but of occupations as well, and many classificatory schemes have been devised (Picou & Campbell, 1975; Holland, 1966; Ossipow, 1973). Occupations can be discriminated by many attributes, but empirical evidence clearly shows that the percent female and perceived socioeconomic status of the occupation exercises powerful effects over occupational choice. It is well-known, for example, that children's occupational choice tend to narrow to a small band of SES fairly early (Haller & Miller, 1971; Haller & Woelfel, 1967; Papalia & Tennent, 1975).

Clearly, individuals array occupations along a prestige hierarchy as well as identify a certain band along this hierarchy as appropriate for themselves (Treiman, 1977). Substantial evidence also shows that this band is highly correlated with future job attainments (Sewell, Haller, and Portes, 1969;

Sewell, Haller and Ohlendorf, 1970; Eckert and Griffin, 1975; Otto and Haller, 1979), and is itself heavily influenced by the status band seen as appropriate for the individual by his or her other significant others (Woelfel & Haller, 1971). In similar fashion, it has been shown that the extent to which a job is considered "masculine" or "feminine" is an important sociopscyhological determinant of job choice (J.C. Woelfel, 1975).

The Problem

It would seem that if one could identify the "bands of acceptability" along each of the several attributes that individuals use to classify or define the occupational domain, one could predict the actual job choice of any individual. Thus, for example, if the job choice for a specific person had to lie between a certain range of prestige, income, male-female incumbance, and perhaps indoor-outdoor activity, and so on, then the number of occupations which could fit all of these constraints would be seen to dwindle until only a few remained from which a choice could be made.

The most immediate problem is that no one knows the complete set of attributes that individuals use in defining occupations. To date, there is substantial evidence that socioeconomic status is central to respondents' conceptual organization of occupational structure (see e.g., Kraus et al. 1978; Saltiel, 1978) and that such distinctions are important for job choice (Holland, 1966). Despite the centrality of this dimension, even mobility researchers have consistently insisted that nonsocioeconomic attributes of occupation are also of significance (Blau and Duncan, 1967, p. 117). For example, both Blau and Duncan (1967) and Klatzky and Hodge (1971) analyzing the same mobility data but with different techniques have concluded that there is at least one other attribute in addition to SES along which intergenerational movement occurs. Similarly, Horan (1974) has shown that both prestige and a caste-based occupational status variable were useful in ascertaining the structure of mobility in an urban Indian city. Finally, Mortimer (1974) has shown that there are several attributes of fathers' work that are transmitted to children, which in turn serve to influence their career orientation. Unfortunately, there has been little in the way of a systematic effort to determine the role of these various attributes in occupational choice.

On logical grounds it might be possible to build up a theory of occupational choice attribute by attribute, but in practice such a program is almost certainly not feasible, particularly if the attributes may be culturally or temporally specific; that is, different from time to time or from place to place. Moreover, there is good reason to believe such a campaign might not be necessary, since many occupational attributes are highly covariant. Thus, for example, one might discriminate one occupation from another on the basis of perceived income, educational requirements, or occupational prestige, but these three attributes are known to be correlated with each other to a fairly high degree, such that they play a relatively redundant role in the classification of occupations. In technical language, each of the attributes along which occupations may be discriminated by some population may be thought of as a vector a_i and the set of all such attributes can be said to constitute a vector space A. This space A is represented by the matrix A, with each of the $\underline{n}$ columns representing one of the $\underline{n}$ attribute vectors which span the space and each of the $\underline{k}$ rows as the position vector or one of the $\underline{k}$ occupations in that space. But since the attributes along which occupations may be discriminated may be covariant, i.e., correlated, the resulting matrix A may be singular; that is, of substantially lower rank than its order.

Mathematically this means that a (smaller) set of orthonormal reference vectors e_i $(i = 1, 2, ..., r)$ may be found where $r<n$. As long as A is a

continuously differentiable manifold, the transformation $AT = R$ exists, where R represents the space spanned by the e_i basis vectors. In a fundamental way, A and R are equivalent; that is, they each contain the same information in that each is a transformation of the other, but the representation R has certain desirable mathematical properties that render it particularly useful and easy to deal with from a computational point of view. Most importantly, insofar as the matrix A is singular, it is possible to represent the interrelations among occupations in the space R even when the projections of the occupations on all the a_i are not known.

Fortunately, there are alternative procedures for generating R (which are discussed below and in more detail in Woelfel and Fink, 1980) which make it possible to determine the coordinates of the occupations in the space — and predict and account for occupational choices — even if none of the a_i are known. Specifically, this research employs a variant of multidimensional scaling (MDS) to generate R. The most significant advantage of such a technique is that one can determine how respondents "organize a set of occupations when left free to use any number of criteria and to select their content" (Kraus et al., 1978, p. 901).

To date, there have been only a few attempts to use such techniques to generate R and to ascertain the underlying attributes. This research has been based on data from respondents who are asked to sort occupations into similar groups or provide estimates of overall similarity between pairs of occupations using a standardized scale. The resulting proximity data is then analyzed using a variety of nonmetric MDS techniques. This research has yielded a number of interesting, but inconsistent findings: Burton (1972) discovered three dimensions: prestige, dependency and skill; Coxon and Jones (1974) have suggested two dimensions: educational requirements and people orientation; and

Kraus et al. (1978) found that a two dimensional solution most satisfactorily fit the data, although only a prestige dimension was identified.

Although interesting, these results have done little more than to verify that prestige (or something closely related) is central to respondents' organization of the occupational domain. While no doubt important, it is particularly unsatisfactory that so few nonsocioeconomic attributes have been clearly identified, and even more disturbing that the resultant spaces are so unstable, even across randomly selected subsamples (see e.g., Kraus et al., 1978). It is simply difficult to believe that individuals in a given society share only the attribute of prestige in their perceptions of the occupational structure.

The precise reasons for these findings are somewhat complex, but it would appear that they are partly a function of the nonmetric techniques of data analysis. In particular, these techniques start with the assumption that the dimensionality of the space should be set at some arbitrarily small value and the observed discrepancies adjusted to fit this constraint as long as the initial order relations are maintained. One of the results of this procedure is a tendency to produce a structure where none exists (Klahr, 1969; McDonald, 1972). Accordingly, the research reported here uses respondents estimates of the distances between occupations (as a ratio-scaled measure) as input, and metric MDS to analyze the proximity data. The resulting degree of precision allows us to show: 1) that the attributes which may account for occupational choice need not be known in advance to permit construction of the occupations domain because they may be inferred, post hoc, from the domain structure; 2) such a structure can be generated from questionnaire data that may be filled out by average respondents in a short time under unsupervised conditions utilizing only written instructions with no intervention by an investigator to answer questions or prompt respondents; 3) the results of such administrations are both precise and reliable, and 4) the spaces resulting from these administrations are valid representations of the occupational structure as perceived by samples of a typical nature. It is to these ends that the present study is directed.

Theory

A theory of occupational choice has already been proposed which suggests that occupations may be arrayed along a set of orthogonal coordinate reference axes which span a multidimensional space (J.D. Woelfel, 1975). Unlike the attribute vectors previously discussed (such as SES, perceived proportion of female incumbants, and the like), or the factors in factor analyses, these orthogonal vectors are thought to have no substantive significance, but serve only a reference function, as do the lettered and numbered grid lines on a street map. Within this space, occupations are arrayed such that the overall psychological or cultural difference between any pair, whatever its basis, is represented by the distance between that pair in the space. The self of each person can also be represented as a point in the same space such that the distance of each person from each occupation is proportional to the degree of psychological "closeness" he or she feels toward each of the occupations. It is consistent with each of the theories cited above to assume the probability an individual might choose any occupation to be inversely proportional to his or her distance from that occupation in the space. Figure 1 is a representation of the first three dimensions of such a space, based on data from Saltiel, 1978.

Figure 1 presents a parallel perspective drawing of the first three dimensions of the occupations space as measured by Saltiel. The intersection of lines at the center of the picture marked "0" represents the origin, or point of intersection of the dimensions. The horizontal line passing through this point and calibrated from -40 through 60 represents the first dimension. Similarly, the vertical line passing through this point represents the second dimension (the calibration numbers are omitted from this dimension for clarity). The oblique line passing through this point and calibrated from 0 through -60 represents the third dimension (positive calibration is omitted for clarity).

The dark circular figures represent the occupations arrayed in this space. The size of the circle is inversely proportional to the distance from the eyepoint of the viewer, so that occupations that are far from the viewer's position seem smaller. ("Pilot," therefore, is the occupation closest to the viewing perspective of the viewer, while "Ranch Hand" is furthest from this point.) Thin vertical lines are dropped from the occupations to the point of projection onto the x-z plane, which is marked with a cross. Those lines which project downward from the x-z plane to the occupations show that those occupations have negative coordinates on the y axis; that is, they lie under the x-z plane.

Following these rules, one may notice that "Pilot" lies in the right foreground, fairly high above the x-z plane, while "Truck Driver," "Mechanic" and "Ranch Hand" form a cluster in the left background above the x-z plane. "Stewardess" and "Secretary," on the other hand, lie in the left foreground quite far below the x-z plane.

[Figure One about here]

Operationally, such a space is obtained quite simply by asking a sample of respondents to evaluate directly the dissimilarity or "distance" between all possible pairs of occupations, and of each occupation and the self, relative to some arbitrary pair of occupations. In practice such measurement devices usually take the form "If occupation A and occupation B are 100 units apart, how far apart are occupation _i_ and occupation _j_?", where i and j are allowed to vary from 1 to k-1 and from _i_ + 1 to k respectively, where k is the number of concepts, including a term designating the self, in the questionnaire. The eigenvectors of the scalar products of the resulting square symmetric matrix constitute the orthogonal reference vectors which span the space, and the projections of each of the occupations (and the self) on these eigenvectors constitute the coordinates of the occupations and the self in the multidimensional space. It is the usual practice of users of this technique to average the dissimilarities matrices over the entire sample prior to calculating the scalar products and eigenvectors, so that the resulting space can be made as reliable as desired.

Psychometricians, themselves frequent users of near relatives of these techniques called multidimensional scaling, often frown on this practice, since it obscures individual differences, but it is quite appropriate for the representation of the collective phenomena of interest to sociologists (Woelfel and Danes, 1979). It is particularly relevant in this case, for as Balkwell et al. (1980) have pointed out, the Wisconsin model of status attainment, upon which this theory of occupational choice is based, rests on the assumption of a shared set of beliefs about occupation.

The theory further suggests that individuals learn to differentiate among the set of occupations — and hence learn the structure of the space — from information they receive about the occupations primarily from conversations and examples of significant others and mass media. Moreover, each person is thought to position himself or herself near the center of the set of occupations that his or her significant others have, by word or action, explicitly or implicitly suggested are potentially appropriate for him or her.

Saltiel (1978), in research directly relevant to this theory, drew the entire population of a consolidated rural high-school district in Montana and, on modified open-ended instruments patterned after the Occupational Aspiration Scale (Haller & Miller, 1971), asked the students to name the occupations they were considering after their schooling was over and when they were 30 years old. From the resulting list he compiled the 34 most frequently mentioned occupations and constructed a 34 item paired comparison Galileotm-type questionnaire of the form described above. Due to the length of the instrument (561 pair comparisons) the questionnaire was divided and one third of it was administered at random to each student. The results were then averaged over the sample and the space depicted in Figure One was constructed by the methods described above. During the same administration, by means of a modified form of the Wisconsin Significant Other Battery (Woelfel & Haller, 1971) he asked the students to name the significant others from whom they had received information about occupations in general. 65 percent of these significant others who were successfully contacted named, on an identical questionnaire, the specific occupations they hoped or expected the children to attain.

Saltiel then took the coordinates of each child's job choices on the first dimension or eigenvector of the space R and averaged them to produce the loading or coordinate of his or her average job choice on the first dimension. Similarly, he averaged the coordinates on the first dimension of the set of occupations selected for the student by his or her significant others. Using the average coordinate of the expected jobs, along with other variables (such as parent' SES) drawn from the occupational attainment literature as independent variables in a linear regression equation, Saltiel was able to explain 53 percent of the variance in the mean coordinate of occupational choice on the first dimension. On the second dimension, the same equation was even more successful, accounting for 86 percent of the variance in mean coordinate of occupational choice on the second eigenvector. (Estimation problems are greatly simplified by this method, since each eigenvector is absolutely independent of each other eigenvector and hence the set of such regression equations is independent and not simultaneous.) R^2s were also impressive for the next four eigenvectors, averaging about .68 for the first three dimensions and .45 for all six eigenvectors which he studied.

These results warrant serious attention for two reasons. First, each regression equation establishes a confidence band perpendicular to its eigenvector within which the student's occupational choice may be seen to lie within a stated probability level. Furthermore, since these eigenvectors are perpendicular, these bands intersect to provide a probability region within which the student's occupational choice may be seen to lie to within a stated level of probability, as Figure 2 illustrates.

The x axis of Figure 2 represents the first dimension of the configuration, while the y axis represents the second dimension. Locations of the occupations within the first principal plane of the (multidimensional) space are given by their coordinates on these dimensions. The point on the x axis labelled x_p represents the predicted value of the average coordinate of the respondent's job choices, while y_p represents the predicted coordinate for the second dimension, following the regression procedures described above. The dashed lines represent the standard errors around those estimates. Thus (given normal statistical assumptions) these bands represent the 68 percent confidence regions for these predictions. This means that there is a 68 percent probability that the actual predicted value for the respondent's average job choice on dimension one lies within the region defined by the two vertical dashed lines, while there is similarly a 68 percent probability that the actual predicted value for the respondent's job choice on the second dimension lies within the region defined by the horizontal lines. The shaded area given by the intersection of these two confidence bands represents the most probable region within which both predictions are satisfied. We might therefore suggest that there is a .68 X .68 = .46 probability that the respondent's actual job choice will be made from within the shaded region. If no occupation lies within the shaded region, then we would predict a job choice near the region. Increasing the size of the region clearly increases the probability that the actual job choice will lie within the region.

Figure 2, of course, represents only the first two dimensions of the occupations space. Including the third dimension would result in the definition of a three-dimensional rectangular region, while adding still more dimensions would define an n dimensional probability region. This, of course, cannot be represented on a flat sheet of paper, but identifying occupations which lie within the region by mathematical means is elementary.

[Figure Two about here]

This means it is possible with these techniques to specify a small set of occupations — possibly even one — from which the individual may be expected to choose to within a specifiable probability level, and in this way the exact job choice of any student can be predicted.

Secondly, and perhaps most important of all, these procedures are completely general and with only trivial modifications can be made to predict not only occupational choices, but any discrete choices whatever. Thus, if the space is populated with political candidates and issues instead of occupations, the discrete voting choice of any public can be predicted (Serota et al., 1978). Similarly, if the space is populated with any discrete behaviors, choices of behaviors can be predicted to specifiable certainty levels, which may indeed be quite high (Woelfel & Fink, 1980).

Although Saltiel's results are strongly supportive of both the general model of occupational choice presented here and its specific operationalization, like any empirical work they leave further questions to be answered. Specifically, 1) Saltiel's sample is a specialized one, being drawn exclusively from a fairly isolated highly rural area in Montana. 2) Although some information relative to the validity of the representation is presented (e.g., Saltiel shows that Duncan's SEI measure correlates about .9 with the first eigenvector of the subset of occupations he measured), sociologists in particular may require more evidence for the reliability of the unfamiliar scaling routine than is available from Saltiel's data. 3) Even though one may be convinced from Saltiel's (or others') data that such a model is possible, some evidence that the procedures are feasible — that is, do not impose unusual respondent burdens or inordinate expenditures would be highly desirable. Finally, as is the case with any empirical work, confirmation of the main element by independent investigators on independent samples is necessary before the results can be taken at face value.

In the present article, therefore, we will attempt to show 1) that the methods used by Saltiel will produce equivalent results when applied to fairly diverse samples (in this case university students in Michigan and Hawaii), 2) That the spaces resulting are reliable over time, 3) That attributes known to span the occupational domain (specifically socioeconomic status and %female) fit into the resulting space, and 4) That the costs of carrying out the measurement program implicit in the model are feasible, both in terms of personal energy and economic costs. The data available to these authors, however, do not permit a replication of Saltiel's substantive predictions of occupational choices, and this must await future research.

Method

Fifteen of the occupations used by Saltiel in his study were formed into a 105 paired-comparison questionnaire. As a standard measure, respondents were instructed to assume that the difference between Postman and Bank Teller was equal to 100 units, and that the differences or distances among the other occupations should be calibrated by this standard according to a ratio rule; that is, pairs of occupations judged to be twice as different as postman and bank teller would be rated 200 units different, while pairs half as different would be rated 50 units apart. (This is the standard Saltiel used, although he set the modulus at 50 rather than 100 units. Work by Gordon (1976) and Gordon & DeLeo (1975) has shown that this difference in modulus affects only the size of the resulting space and leaves its relative shape invariant.) Sixty-four students from the introductory communication class at Michigan State University took the questionnaire home with them and filled it out as part of a voluntary extra-credit scheme which also required them to keypunch the results of their questionnaire in return for a modest increment (less than 1%) of their Communication 100 grade. Data were read onto a computer file, and experienced graduate assistants corrected keypunch errors by reference to the original questionnaires. The following year, this procedure was repeated exactly, and 50 additional students filled out the questionnaires. Simultaneously, 81 additional students from introductory history, psychology and English classes at the University of Hawaii filled out identical forms, although no incentive was provided to these students. The questionnaires from the Hawaiian sample were professionally keypunched and verified. All in all, 195 questionnaires were gathered from the two independent sites over the two-year period.

Reliability

The first step in the analysis procedure is to average the pair-wise dissimilarities across all sample respondents to yield an average dissimilarities matrix. Since the average dissimilarities matrix is the starting point for further analysis, it is important to establish the reliability of these means. A convenient and scale-free statistic for this purpose is the relative error (VNR, 1977), which is given by the standard error divided by the mean. This figure is multiplied by 100 to yield the percent relative error. Percent relative error was accordingly calculated for each of the 120 means within each of the three datasets. These errors were then themselves averaged within each of the three datasets. For the first dataset (Michigan 1976-77) the average relative error was 10.49%; for the second (Michigan 1978-79) the average relative error was 11.48%, and for the third (Hawaii 1978-79) the average relative error was 8.50%. Finally, the three datasets were themselves combined, and percent relative errors for the 120 mean dissimilarities in the aggregate dataset (N=193)[2] were calculated. These errors were then averaged and the resulting average relative error was 5.58%. These are very impressive figures by current standards, particularly since they are achieved for ratio-type scales which, while universally acclaimed as desirable, are often (erroneously) considered to be subject to reliability problems when used to measure social data.

As impressive as these figures may be, they do not speak to the question of the comparability of the datasets, nor do they take into account the reliability of the axes or dimensions of the configuration, which are fundamental to the theoretical operations described earlier. In order to assess these reliabilities, the eigenvectors of each of the configurations were calculated. Each eigenvector may be represented as a column of a k x r matrix $R^{\mu}_{(\alpha)}$ where the subsript α (in parentheses to show it is not a tensor index) represents the concept — in this case occupation — to which the loading refers, and the superscript μ indicates the eigenvector or axes to which we refer. Thus α ranges from 1 to k, and μ ranges from 1 to r when there are k occupations in an r dimensional space.

Because the orientation of the eigenvectors of any configuration is arbitrary, the set of eigenvectors of the second dataset were rotated to a least-squares best fit on the eigenvectors of the first set, and the eigenvectors of the third set (Hawaii) were rotated to least-squares best fit with those of the second dataset (Woelfel, Holmes & Kincaid, 1979)[1]. This operation in no way compromises the original data, since all the original pairwise distances remain invariant under this transformation, just as the distances among objects in a picture remain the same when that picture is turned upside down, but it does eliminate purely artifactual differences in orientation of axes. Once this has been accomplished, correlations among corresponding axes were calculated. Since correlations are actually cosines of angles between the variable vectors correlated, these correlations are indicators of the extent to which the axes are oriented in the same directions. Correlations of 1.0 for all corresponding pairs would indicate that the spaces are identical in shape, with each point occupying the same relative position in each space. These correlations are extremely high, indicating that the three spaces corresponding to the three administrations are very similar.

This high degree of consistency across the three samples, is particularly interesting in light of the Kraus et al. (1978) findings. Based on a Smallest Space Analysis of proximity data for 25 occupations, Kraus examined the loadings on the first two dimensions across three randomly selected subsamples. The data showed that the loadings on the first dimension were invariant across all three. But the correlations between the second dimension coordinates were extremely low. And, roughly similar results were obtained when the sample was broken into a number of subdivisions such as male-female, high and low education, etc.

Tables 1 and 2 show the correlations between corresponding rows of the matrices representing the spaces in the two Michigan datasets (Table 1) and the second Michigan and Hawaii datasets (Table 2). These rows represent the position vectors of the occupations in the space, and thus a high correlation for any row with its counterpart in another dataset indicates that the concepts corresponding to these rows lie in the same directions in the spaces.

Similar but not identical information about the stability of the locations of each of the concepts across the three datasets is given in Tables 3 and 4. These tables give the shortest-path distance between each concept in a dataset and its counterpart in an adjacent dataset. Table 3 gives this information for the two Michigan datasets, while Table 4 provides the same information for the 1978-79 datasets in Michigan and Hawaii. Altogether these tables show very high stability across the three datasets, with _nurse_ the least stable occupation and _hairdresser_ the most stable. Both comparisons (i.e., Michigan-Michigan and Michigan-Hawaii) show an _imaginary_ distance between the respective locations of _construction worker_, which may be interpreted as indicating a relatively high level of ambiguity of meaning for this occupation. the ambiguity may not be interpreted as measurement error, however, since the measured ambiguity itself is stable across the three datasets (Barnett and Woelfel, 1979).

To establish the reliability of each of the individual coordinate loadings themselves, the R.M.S. (root mean square) deviations of each coordinate from its counterpart in the adjacent dataset were calculated (Woelfel et al., 1978). This means, in practice, that the coordinate of the first occupation on the first axis of the second dataset was substracted from the coordinate of the first occupation on the first axis of the first dataset, and this difference was squared. The same operation was then performed for the first coordinate of the occupation on the second axis, and so on through all corresponding coordinates. These squared deviations were then summed, the result was then divided by the number of axes and the square root of the result calculated to yield the R.M.S. deviation of the coordinates of the first occupation. This figure is an estimate of the precision of each coordinate loading for the first occupation across all the axes.

In the notation introduced earlier, the R.M.S. deviation for the coordinates of the th occupation across two datasets $\sigma_{R_{(\alpha)}}$ is given by

$$\sigma_{R_{(\alpha)}} = [\Sigma_{\mu=1} \quad (R^{\mu}_{(\alpha)} - \hat{R}^{\mu}_{(\alpha)})^2 \ /r \ ]^{\frac{1}{2}}$$

where $R^{\mu}_{(\alpha)}$ = the coordinate loadings of the αth occupation in the first dataset

$\hat{R}^{\mu}_{(\alpha)}$ = the coordinate loadings of the αth occupation in the second dataset

r = the number of dimensions in the space.

These figures were calculated for each occupation separately and averaged to yield a R.M.S. deviation for the coordinates of 5.51 for datasets one and two, which may be taken as test-retest reliability estimates in this case. Under reasonable assumptions, these figures consevatively approximate the 68%

confidence interval for the coordinates and the 99% confidence interval is roughly double this figure. Since the range of the first factor is about 260 units, this means that each coordinate on the first factor is defined to within about 2% of its range within each dataset. These figures show very clearly that the coordinates of the occupations in the space can be determined to very high levels of precision by current standards. (Although the process of measuring deviations of adjacent coordinates from each other rather than from their collective mean, as is typical, is appropriate given the nature of these datasets, nonetheless it is a conservative procedure, and traditional procedures, had they been applied, would necessarily have produced even smaller estimates of the standard errors.)

This information allows us as well to make an estimate of the number of dimensions which span this configuration of occupations. Since each of the dimensions is a vector in a 15 dimensional space (where 15 is the number of occupations in this study), its length 1 is given according to the pythagorean theorem as the square root of the sum of the squares of its coordinates, or

$$1_{\mu} = [\sum_{\alpha=1}^{k} R^{\mu}_{(\alpha)} \quad R^{\mu}_{(\alpha)}]^{\frac{1}{2}}$$

The lengths of each of the axes of each of the sample's spaces are given in Tables 3 and 6 as the magnitudes of the column vectors. (Each dimension is represented as a column vector of the matrices representing the spaces, as we have suggested.) The absolute standard error Δa_{μ} for the square root of the sum of squares of a set of elements R^{μ} each of which is an associated error of Δa is given by

$$\Delta a_{\mu} = \frac{\Delta a}{2} [\sum_{\alpha=1}^{k} \Delta a2 \quad |R^{\mu}_{(\alpha)} \quad |^{\frac{1}{2}}$$

Carrying out this work for the first dimension of the first Michigan dataset yields an error of 19.33, which means that the approximate 68% confidence intervals for the lengths or magnitudes of the dimensions are between $\pm$ 19.33 units of the given figures in Tables 5 and 6, and the 99% confidence intervals are approximately the given figure $\pm$ 38.66. This means that all except the 11th, 12th and 13th dimensions of all three spaces are significant at better than the .01 level. Statistically speaking, we cannot reject the hypothesis that 132 dimensions are required to represent the configuration of these 15 occupations. Of course, adding additional occupations to the space could not result in a <u>reduction</u> of this rank, but might require yet additional dimensions, so it is accurate to say that the domain of occupations is at a minimum 12 dimensional[2] based on these data. It is important to note that we do not expect (as is common in factor analysis, which is a related technique — cf. Woelfel et al., 1975) that these dimensions ought to correspond to any of the original attribute vectors. This, in fact, would be an extremely fortuitous coincidence. What we do expect, however, is that the attribute vectors (like SEI, % female in job, relative % indoor work, etc.) lie at designatable and stable angles to these orthogonal dimensions, such that the functional relations between attributes and orthogonal reference vectors may be established once and for all with perhaps only periodic updates required to deal with relatively slow cultural changes in the basis on which societies classify occupations. To the extent to which such stable functional relations can be found, we consider the space to be a valid representation of the occupational domain.

Validity

The space generated by these procedures is intended to serve as a region within which attributes already known to discriminate occupations (such as prestige, etc.) may be arrayed. In this way. the space serves as a convenient symbolic representation of the array of both occupations and attributes. Evidence for the validity, both of this concept and the operational measures for achieving it, is thus given by the extent to which such attributes may be fit reliably within the resulting space. Since each dimension of the space is orthogonal to all others, the orientation of any attribute, relative to any dimension is therefore independent of its orientation to each of the others. The linear relation of an attribute to the overall space is given therefore by r independent bivariate regression equations of the form

$$y = a_{(\mu)} + b_{(\mu)}R^{\mu} + e$$

where y = a vector of scores of the occupations on an attribute, i.e., either SEI or percent female,

$a_{(\mu)}$ = the intercept of u on the μth dimension, i.e., $y = a_{(\mu)}$ when $R^{\mu}=0$ (μ is in brackets to indicate it is not a tensor index),

$b_{(\mu)}$ = the slope of y on the μth dimension, (μ is in brackets to indicate it is not a tensor index),

R^{μ} = projections of the k occupations on the μth dimension.

e = a least-squares error term.

Two well-known occupational attributes are measured here. The Standard International Occupational Prestige Score (SIOPS) is taken from Treimann (1977), and % female in each was obtained from the 1970 United States Census data for the State of Michigan (there were very few occupations which were analyzed by sex in the Hawaii State Census, but the percentages which were available were comparable to those given in the Michigan Census (e.g., secretary - .957 Hawaii, .977 Michigan), and both Hawaii and Michigan percentages compared favorably with national data (secretary - .99 U.S.).

Table 7 represents the coefficients of these equations. As this table shows, both attributes fit well within the space, with the Treimann SIOPS scores falling at an angle of about 28^{o} from the first dimension, while the % female attribute lies essentially within the subspace generated by the 3rd, 4th and 5th dimensions. This is further confirmation of the centrality of prestige in perceptions of occupational structure.

Since the dimensions of the space are orthogonal to each other, the multiple correlation of an attribute with any subset of the dimensions is given by

$$R = \left(\sum_{\mu=j}^{\rho} r_{\mu}^{2}\right)^{1/2}$$

where R = the multiple correlation of an attribute with the μ th through the ρ th dimension.

r_{μ} = the zero-order correlation of the attribute with the μ th dimension.

Carrying out this work shows that the multiple correlations (R) of the SIOPS with the 5 best-fitting dimensions are equal to .974, .969 and .990 for the three datasets, while the multiple correlation of % female with the 5 best-fitting dimensions is .984, .884 and .986 for the three datasets.

These data indicate clearly that the attribute vectors SIOPS and % female fit into the space, and, moreover, that the orientation of the two attributes is nearly the same to within only a few degrees in all three samples. Figure 3 shows the orientation of the SIOPS vector within the neighborhood of these fifteen occupations, as it is defined by the first three dimensions of space. Figure 4 shows the orientation of the % female attribute within the same neighborhood. (The two attributes correlate .07 in this sample, and thus lie at an angle of 86^{o} to each other, as these diagrams illustrate.) Since by both Figures 3 and 4 depict only the first three dimensions of the space, they are therefore only approximations of the overall structure. But they are still helpful in visualizing the relation of these two attributes to the general structure of the occupations.

Implications

This article has argued for a general theory of choice behaviors which is based on a spatial model in which objects, attributes and selves are arrayed in a multidimensional Riemann space. The meaning of any object is given by its location in the space relative to all the other objects (both attributes and selves may be thought of as objects in a most general sense). The location of objects (including the self) within this space is a result of definitions from others and from self-reflexive activity about the relationships among the objects. Within this model, distance of any object from the self is held to be predictive of approach behavior toward the object.

These ideals were illustrated in the present case with data taken from the domain of occupational choice. Evidence from three samples of respondents in two diverse states at a maximum interval of one year indicate 1) that the methods proposed for constructing such spaces yield reliable and highly precise spaces; 2) that the structure of the space is very stable across a year's time; 3) that the structure of the space is very similar across both Michigan and Hawaii students, even though these two states are probably more different from each other than most pairs of U.S. states; and 4) the space so constructed contains attributes known to discriminate occupations in samples like those investigated here, namely prestige and percent female. The orientations of these attributes within the space are stable to precise tolerances across the year interval and across the two different states. Moreover, extensive experience not only from this study but over several years of work has shown that the respondent burden and investigator effort required to generate such a space is not unduly high, and in fact may even offer some advantage in economy over more typical researches.

This model also affords the opportunity for highly precise and sophisticated occupational counselling. Since the measured distances among occupations in the space are good indicators of culturally perceived similarities among those occupations in a global sense, that is, considering all possible ways in which they might differ, counsellors have good grounds for suggesting alternative occupations to those students who aspire to jobs that are overfilled or in which occupational opportunities are limited. Once the occupations space has been mapped, for example, it is an elementary exercise to compile an alphabetical listing of all jobs. Included in the listing of each job might be a list of its ten "nearest neighbors" in the occupations space. Of course, even now an experienced counsellor with a good knowledge of the occupations domain does much the same thing in recommending alternative jobs the aspirant may find similar to the specific one he or she has considered, but the existence of such a reference space not only would improve the precision with which this can be done, but would also allow counsellors with more limited expertise and experience to provide useful counselling.

Even more precise methods could be devised which required a job aspirant to fill out a form identical to the one on which the cultural estimates are made. The results of these measurements would yield a fairly good estimate of the aspirant's own position within the occupational space, and with very limited training, counsellors could suggest occupations close to the aspirant's self position. Even given our limited present understanding of these spaces the general likelihood of making a good match using these methods seems quite good.

By far the most important implications of these findings, however, are their implications for self theory. As we have suggested, both the objects of experience and the self may be arrayed mathematically in a state space or attribute space. Within this space, objects closest to the self are most consistent with the self. Although traditional sociological practice has emphasized psychological or cultural attributes (such as socioeconomic status, or race) as the basis of such spaces, the problems of operationally defining such spaces are very serious, since all the attributes relevant are not usually known, and moreover, the mathematics of such oblique spaces is somewhat tedious.

This paper shows that an equivalent state space or attribute space can always be constructed by the method of ratio pair comparisons whether or not the attributes are known. Moreover, the space resulting from the pair comparisons method is mathematically much more tractable than the traditional practice, particularly since statistical estimation procedures can always be reduced to the OLS case. As Saltiel has already shown, such a space can be made to yield precise estimates of the exact categorical job choice of individuals. Our data indicate that Saltiel's results are generalizable across time and across two different geographic and cultural contexts. Although we have illustrated the way in which this theory can deal with discrete choice situations only for the case of occupational choice, both theory and methods are completely general and can be applied to any discrete choice situation whatever. Despite the deficiencies of sampling and generalizability in the present data, the precision and stability of these results over time and across samples are impressive and clearly warrants further investigation.

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FOOTNOTES

[1]The Galileo™ version 4.5 computer program at the East-West Center for analysis. (Subsequent analysis on the later Galileo™ version 5.1 computer program at the State University of New York at Albany yielded identical results.) All results reported in this paper are based on these analyses.

[2]$N \neq 195$ because not all respondents answered every item.

Table 1. Concept Position(Row) Vector Correlations Between Time 1(Michigan, 1977-78) and Time 2(Michigan, 1978-79)

Concept		T 1 Magnitude	T 2 Magnitude	Correlation	Angle
1	Accountant	135.13	148.25	.974388	13.0
2	Teacher	79.96	118.13	1.015541	13.0
3	Hairdresser	173.73	162.77	.992251	7.1
4	Doctor	169.11	164.18	.982878	10.6
5	Secretary	121.93	136.29	.958856	16.5
6	Politician	137.54	150.39	.948095	18.5
7	Journalist	129.34	141.58	.979035	11.8
8	Carpenter	124.27	141.67	.983564	10.4
9	Farmer	144.29	163.10	.982833	10.6
10	Plumber	134.86	161.10	.994420	6.1
11	Artist	145.09	156.46	.982668	10.7
12	Construction	147.21	153.30	.999735	1.3
13	Veterinarian	148.16	170.42	.964460	15.3
14	Computer	133.28	142.02	.957581	16.7
15	Nurse	131.68	136.04	.908069	24.8

Table 2. Concept(Row) Vector Correlations Between Michigan (1978-79) and Hawaii (1978-79)

Concept		T 2 Magnitude	T 3 Magnitude	Correlation	Angle
1	Accountant	148.25	125.81	.898487	26.0
2	Teacher	118.13	94.98	.879393	28.4
3	Hairdresser	162.77	158.78	.980808	11.2
4	Doctor	164.18	154.82	.981605	11.0
5	Secretary	136.29	129.26	.921252	22.9
6	Politician	150.39	146.71	.955089	17.2
7	Journalist	141.58	119.57	.981585	11.0
8	Carpenter	141.67	122.94	.977914	12.1
9	Farmer	163.10	141.79	.956254	17.0
10	Plumber	161.10	139.60	.955469	17.2
11	Artist	156.46	127.31	.980777	11.3
12	Construction	153.30	141.14	1.000445	11.3
13	Veterinarian	170.42	145.25	.948858	18.4
14	Computer	142.02	136.60	.947428	18.7
15	Nurse	136.04	129.90	.914369	23.9

Table 3. Distances Moved in the Interval Between 1977-78 and 1978-79 for Michigan University Students

		Real	Imaginary	Riemann
1	Accountant	47.324	39.917	25.420
2	Teacher	42.646	34.471	25.109
3	Hairdresser	28.634	27.629	7.519
4	Doctor	35.334	16.983	30.985
5	Secretary	42.818	16.534	39.497
6	Politician	50.767	22.655	45.432
7	Journalist	33.599	18.391	28.119
8	Carpenter	40.317	27.747	29.250
9	Farmer	35.733	11.049	33.982
10	Plumber	42.357	29.857	30.044
11	Artist	32.762	12.538	30.268
12	Construction	27.569	34.905	-21.408
13	Veterinarian	49.681	16.478	46.868
14	Computer	44.039	24.406	36.657
15	Nurse	61.822	23.678	57.108

Table 4. Distances Between Locations of 15 Occupations in Michigan (1978-79) and Hawaii University Students (1978-79)

		Real	Imaginary	Riemann
1	Accountant	68.945	22.205	65.272
2	Teacher	65.704	36.393	54.704
3	Hairdresser	37.899	27.130	26.463
4	Doctor	36.661	22.789	28.717
5	Secretary	53.824	12.317	52.395
6	Politician	44.887	10.000	43.759
7	Journalist	33.573	10.382	31.927
8	Carpenter	37.084	16.888	33.016
9	Farmer	50.420	12.681	48.800
10	Plumber	63.875	40.985	48.992
11	Artist	43.927	23.699	36.986
12	Construction	56.560	57.249	-8.857
13	Veterinarian	56.483	18.968	53.203
14	Computer	46.297	23.580	39.842
15	Nurse	56.546	13.452	54.923

Table 5. Dimension(Col. Vector) Correlations Between Time 1(Michigan, 1977-78) and Time 2(Michigan, 1978-79)

Dimension	T 1 Magnitude	T 2 Magnitude	Correlation	Angle
1	315.27	332.38	.992677	6.9
2	256.34	274.44	.989647	8.3
3	207.14	207.40	.978463	11.9
4	187.05	181.85	.974833	12.9
5	136.35	146.70	.904189	25.3
6	111.95	135.60	.940643	19.8
7	110.44	142.13	.941392	19.7
8	90.57	99.61	.719844	44.0
9	71.03	109.04	.962636	15.7
10	52.34	96.29	.917138	23.5
11	.00	12.32	*******	****
12	.86	.00	.394126	66.8
13	33.95	21.36	.470628	61.9
14	73.00	74.71	.732210	42.9
15	87.47	90.78	.833769	33.5

Table 6. Dimension(Col. Vector) Correlations Between Michigan (1978-79) and Hawaii (1978-79)

Dimension	T 2 Magnitude	T 3 Magnitude	Correlation	Angle
1	332.38	309.41	.990987	7.7
2	274.44	244.13	.981299	11.1
3	207.40	189.64	.982003	10.9
4	181.85	169.83	.959307	16.4
5	146.70	134.86	.912792	24.1
6	135.60	124.41	.930673	21.5
7	142.13	125.87	.947615	18.6
8	99.61	78.87	.625186	51.3
9	109.04	78.20	.374844	68.0
10	96.29	94.94	.847129	32.1
11	12.32	28.45	.759091	40.6
12	.00	.62	.358273	69.0
13	21.36	24.44	.677322	47.4
14	74.71	82.41	.607391	52.6
15	90.78	101.94	.860312	30.6

Table 7. Orientations of Treiman SEI Measure and % Female in Occupation in a Domain of 16 Selected Occupations for 3 Independent Samples (Manual = 999)

			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
SEI	MICHIGAN '77	a	50.31	49.74	49.70	49.84	49.38	49.79	49.78	49.68	49.77	49.79			49.67	49.80	49.60	49.76
		b	.15	0.00	.06	.01	-.08	-.02	.09	.07	-.02	.14	0	0	.08	.08	-.11	-.06
		r	.89	.04	.23	.04	-.19	-.05	.19	.13	-.03	.15			.05	.11	-.18	-.15
		α	26.57	87.66	76.94	87.97	101.17	93.09	79.13	82.77	91.85	81.49			87.39	83.85	100.37	98.55
	MICHIGAN '78	a	50.40	49.69	49.74	49.99	48.83	49.82	49.82	49.75	49.63	49.82	49.75		49.79	49.79	49.73	49.71
		b	.15	.02	.06	.04	-.15	-.03	.06	.07	.06	.05	.03	0	.24	.08	-.03	-.09
		r	.89	.08	.23	.12	-.31	-.07	.15	.10	.09	.10	.02		.12	.13	-.05	-.17
		α	27.49	85.45	76.55	82.94	108.14	93.82	81.37	83.98	84.93	84.30	89.11		83.33	82.63	92.83	99.94
	HAWAII '78	a	50.24	49.77	49.76	50.53	48.89	49.79	49.85	49.77	49.76	49.80			49.73	49.78	49.62	49.69
		b	.14	0.00	.06	.05	-.13	-.03	.04	.03	-.02	.08	0	0	.43	.09	-.08	-.07
		r	.87	0.00	.23	.16	-.27	-.08	.12	.05	-.03	.15			.18	.13	-.14	-.15
		α	29.29	90.09	76.72	81.08	105.77	94.60	83.32	87.15	91.95	81.23			79.69	82.61	98.28	98.91
% FEMALE	MICHIGAN '77	a	36.40	37.09	33.95	33.52	37.16	36.10	35.48	34.81	36.16	36.24			36.17	36.18	36.22	36.39
		b	.07	-.25	.22	-.42	.15	.05	-.34	-.10	.22	.20	0	0	-.28	0.00	.05	.22
		r	.18	-.51	.34	-.49	.12	.05	-.36	-.07	.18	.15			-.05	0.00	.03	.19
		α	79.37	120.99	69.93	119.58	83.01	86.99	110.98	98.11	79.57	81.62			92.59	89.69	88.22	79.15
	MICHIGAN '78	a	36.30	37.06	35.79	33.15	36.05	36.19	36.08	33.98	36.12	36.22			37.88	36.24	35.79	36.14
		b	.04	-.27	.28	-.43	-.02	-.05	-.47	-.36	.26	.37	0	0	-1.46	.21	-.09	.25
		r	.10	-.51	.44	-.51	-.02	-.04	-.39	-.24	.14	.15			-.32	.11	-.05	.23
		α	84.28	120.68	63.63	120.51	91.04	92.22	112.87	103.69	82.04	81.58			108.90	83.47	92.79	76.42
	HAWAII '78	a	36.41	37.48	36.03	33.63	36.22	35.83	35.74	36.15	35.71	36.80	36.34		36.20	36.19	36.02	36.19
		b	.06	-.31	.29	-.47	.01	.18	-.45	0.00	.20	.60	-.43	0	.51	.18	-.09	.08
		r	.15	-.56	.41	-.53	.00	.16	-.43	0.00	.11	.43	-.09		.09	.11	-.06	.06
		α	81.63	124.18	65.63	122.08	89.45	80.68	115.16	90.30	83.76	64.75	95.14		84.56	83.66	93.73	86.70

LIST OF FIGURES

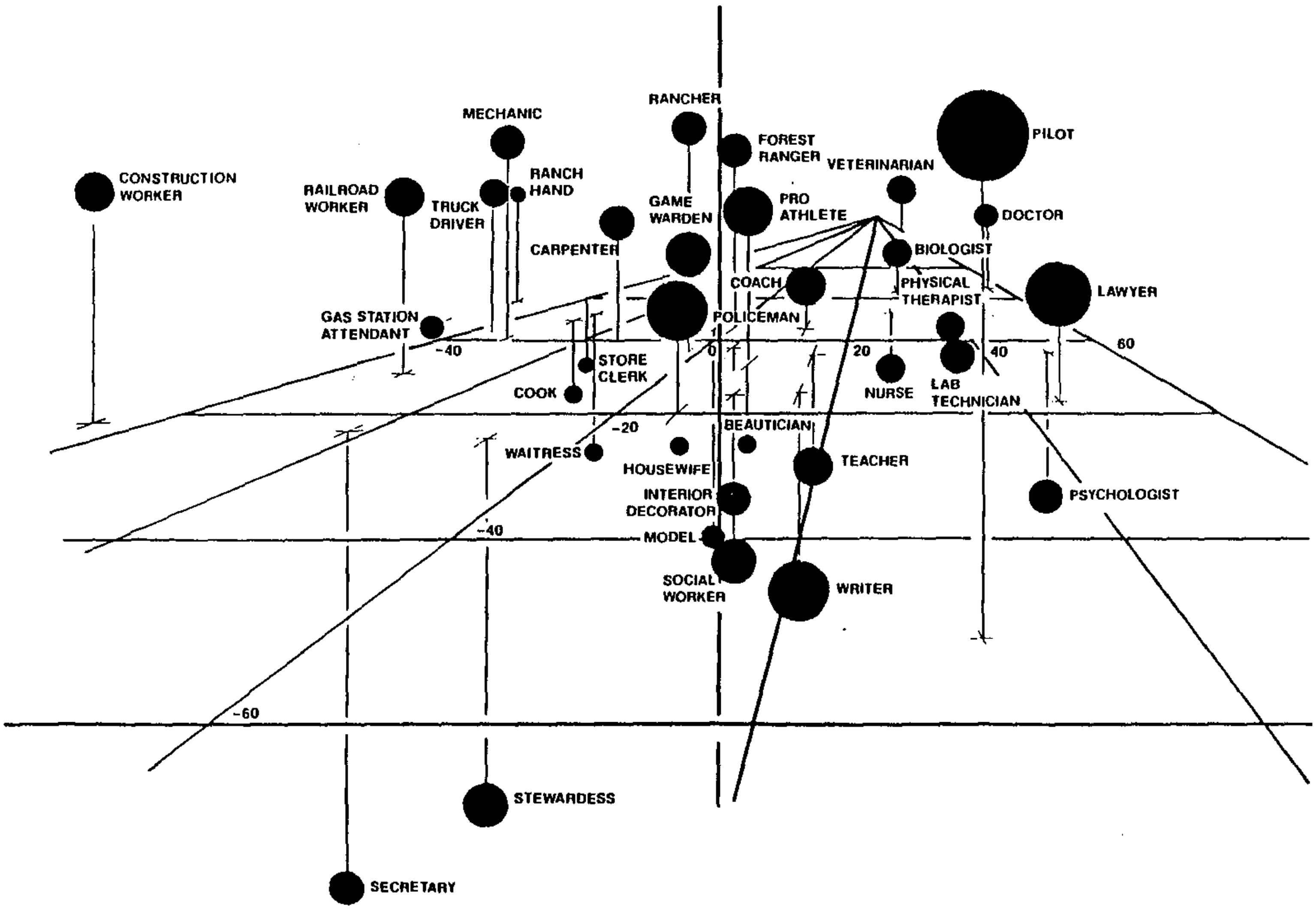

Figure 1. The First Three Dimensions of an Occupations Space in Parallel Perspective (Adapted from Saltiel, 1978)

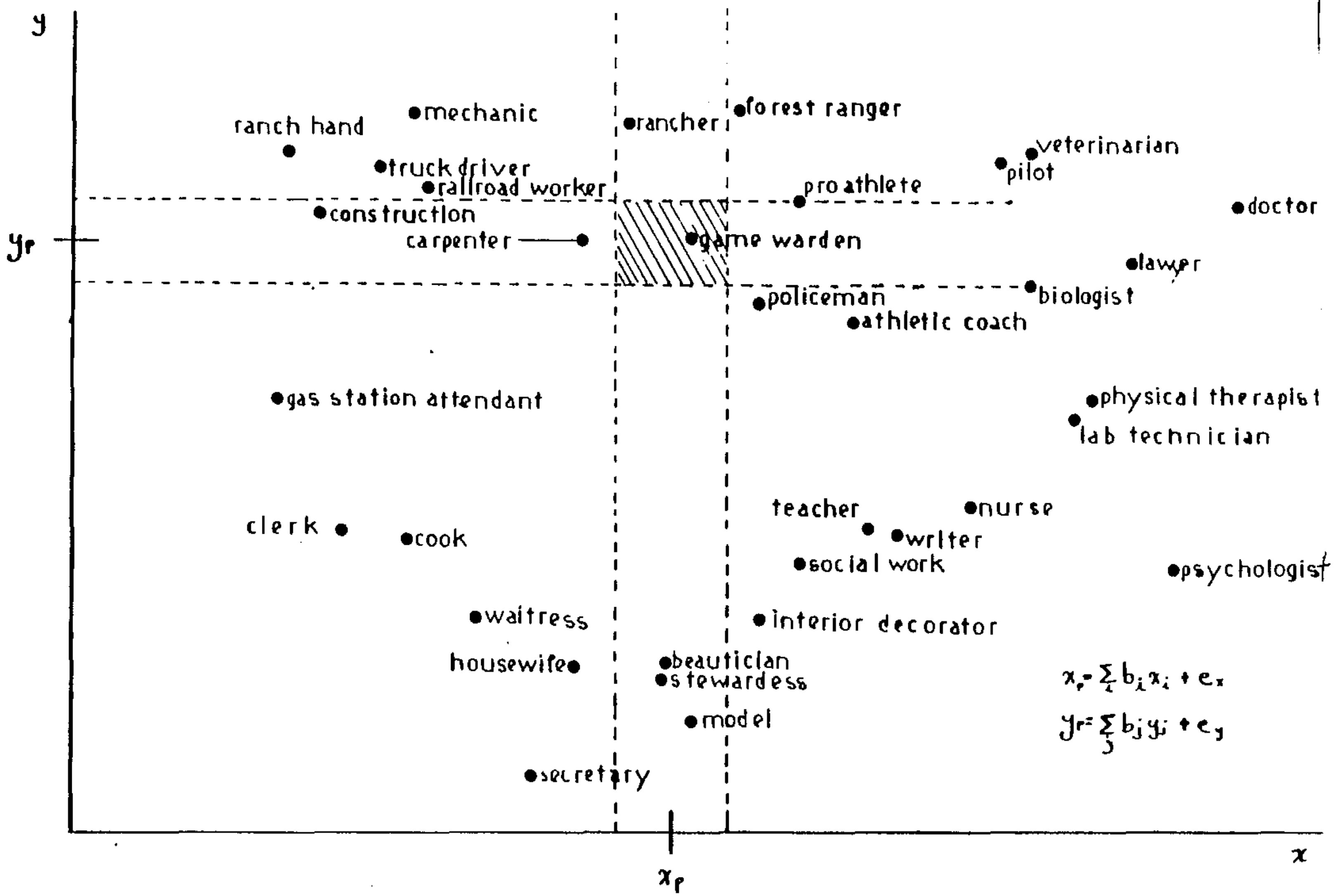

Figure 2. The Most Probable Region of Occupational Choice as Predicted by the Average Coordinates of the Respondent's Job Choices on the First Two Dimensions.

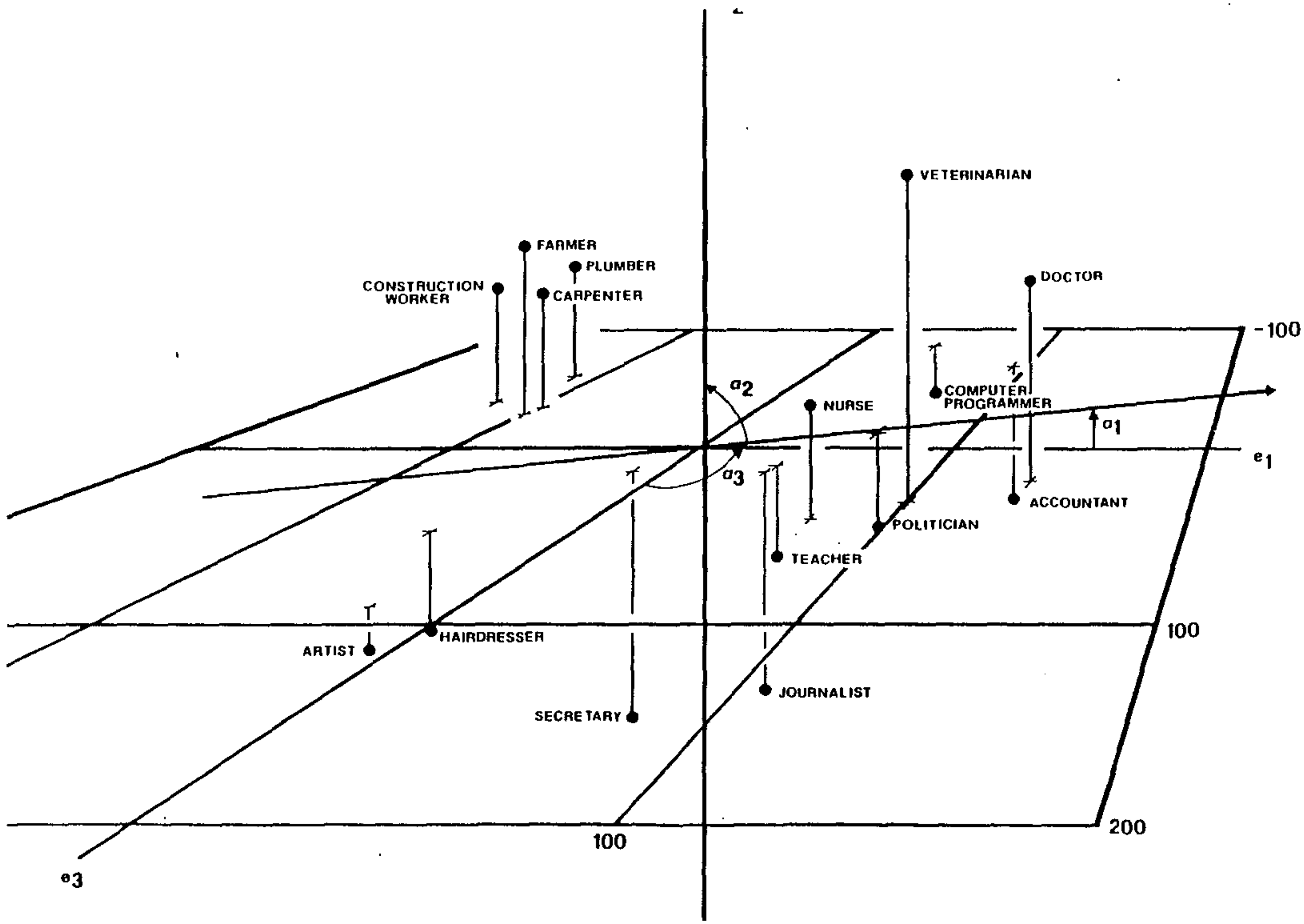

Figure 3. Orientation of the Standard International Occupational Prestige Score Vector in the First Three Dimensions of the Occupations Space.

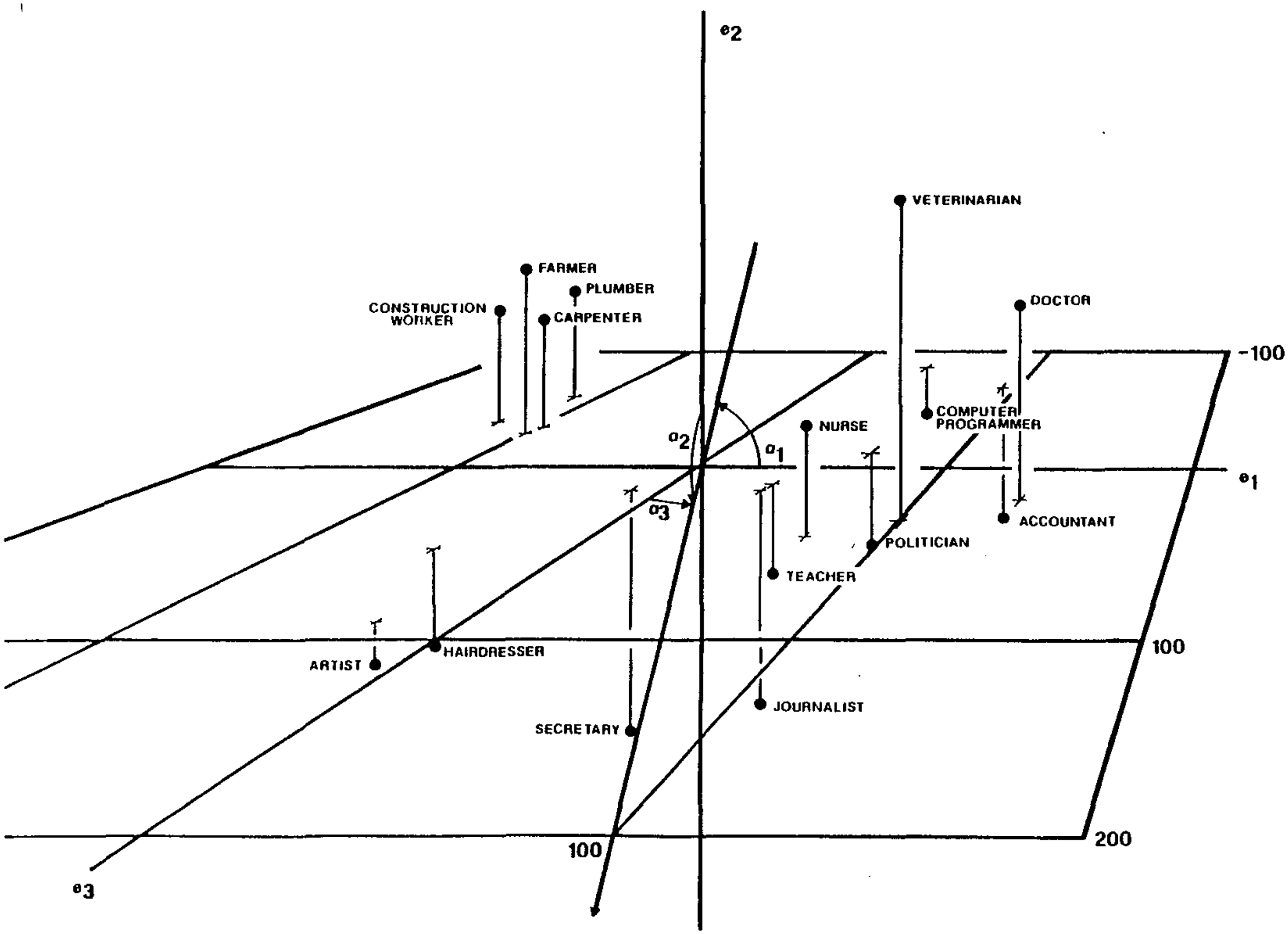

Figure 4. Orientation of the Proportion of Females Vector in the First Three Dimensions of the Occupations Space.