A statistical model of child placement decisions

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Earlier computer models of the child placement process focused on the referring party's description of a child's characteristics and blamed lack of success on the absence of a generalizable expertise in placement decisions. By emphasizing the admissions criteria of residential facilities, the discriminant analysis techniques described in this article produced a model whose placement recommendations matched well with actual placements.

Since the publication in 1959 of Maas and Engler's pioneer work *Children in Need of Parents,* many researchers have explored the child placement process.[1] A recurrent theme in these studies is the need to identify and articulate criteria used to make placement decisions.[2] After a comprehensive review of such studies, Mayer and his colleagues concluded that "there is no clear conception as to what facilities can serve which disturbed child."[3] In 1978, Kadushin expressed a similar concern about the lack of valid justifications for child placement decisions:

> Social workers are still groping for a clear, reasonably well-validated answer to the classic question involved in a referral decision: "What kind of children are best served in what kind of facilities?"[4]

It is often debated whether practice knowledge is sufficient to answer this question or whether the requisite knowledge exists but needs to be systematized and articulated. The study reported in this article suggests that an investigation of this decision-making issue should begin by identifying patterns in the practice of child placement.[5] If patterns can be discerned, a framework can be developed to guide future decision making.

In 1979, Jaffee suggested that decision making for child placement could be incorporated into a statistical computer model. In developing one of the earliest computer models of the child placement process, Jaffee reasoned as follows:

> If detailed information about a particular child and his or her family were available and other information about the kinds of placements most beneficial for certain children were available as well, both sets of facts could be compared to determine the best possible placement for the child in question. This is basically the process caseworkers go through in planning with clients, and is precisely the same process used by computers.[6]

The data base Jaffee used to construct the model included 110 descriptors of each child studied and of the child's family and preplacement and postplacement histories. Data were collected seven years after the cohort studied had been discharged from the large institution where each child had

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lived for at least two years. Jaffee's methodology relied on the opinions of child placement experts who ranked each of the 110 descriptors on two dimensions—their general importance in the placement decision and their relevance for each of the six types of care available: the child's own home, a relative's home, a foster family's home, a kibbutz, adoption, or institutional care. The data items were entered into a computer that multiplied each item's score on the importance dimension by its score on the relevance dimension and summed the results to form a rank-ordered list of placement recommendations.[7]

In an attempt to validate his model, Jaffee had a panel of consultants and the computer model independently recommend placements for samples of children. The consultants were graduate social workers with extensive experience in child welfare services. The children had already been placed, and those placements were contrasted with the recommendations suggested by both the consultants and the computer model. A chi-square analysis revealed significant differences between the recommendations and the actual placements.[8]

The model produced by this methodology did not sufficiently mirror professional recommendations or actual practice to be an effective tool for planning child placements. Jaffee concluded that "the problem in using computers for clinical decisions lies in the degree of difficulty involved in identifying the values and principles underlying clinical practice.[9] Other researchers reached similar conclusions after finding a lack of consensus among social workers about which placements are best for which children.[10]

This evidence might be taken to suggest that social workers have yet to develop a generalizable expertise regarding child placement decisions, but a closer examination of the placement process reveals that previous modeling efforts did not focus on the correct set of decision makers. In practice, a caseworker searches for an appropriate placement for a child by first scanning the alternatives and then referring the child to the admissions specialists who act as gatekeepers at each placement facility. These specialists, whose province it is to know what types of children are best served by admission to their program, are ultimately responsible for deciding whether to admit the child. Therefore, a computer model that effectively predicts the probability of a child's admission to an array of residential programs must replicate the expertise of the decision makers at each institution rather than the judgments of the caseworkers who refer children for admission.

MODEL

The objective of the study reported here was to develop a technology for matching children and placement alternatives and to incorporate that technology into a computer model that would provide a rank-ordered listing of placement alternatives based on the descriptors of a particular child. The value or weight attached to any single characteristic of the child for a particular placement alternative was developed by a statistical analysis of placements already in effect. Patterns of descriptors were identified that characterized children admitted to the different residential programs in the study.

Jaffee's objective of determining the "best possible placement" defies direct operationalization. The best possible placement would be the one that produced the greatest possible success or benefit for the child in question. In the absence of outcome studies, the question appears unanswerable. Even with outcome studies, it is difficult to know whether a final determination of success or best-possible outcome is either generalizable or clearly attributable to the treatment received by the child in placement.

In an attempt to replicate existing placement decisions, the authors' model treated a child's actual placement as a satisfactory or reasonable alternative for the child's needs. Although there may be other facilities that could serve a child equally well or better, it was necessary to assume that the majority of children are placed in programs that take into account (1) the need of the child for care and treatment and (2) the need of the program to maintain a stable and viable milieu.

Therefore, the authors sought to develop a model that would recommend reasonably good alternatives for a child needing residential care and replicate the existing patterns of placements at the facilities included in the study. A placement model could not be better than the combination of practice interventions that produced the present system of care.

The assumptions made in operationalizing the problem were based not only on the criteria of reasonableness, but on the constraints of practicality. It could be argued that the placement process would be better modeled by including both decisions to accept or reject the children who are referred. Whether such a procedure would produce better results is moot because intake materials on children who are not accepted for placement are not routinely or universally retained by these institutions.

Thus, modeling the child placement process was operationally defined as modeling the existing system of care. By focusing on actual admissions, the authors directed the modeling effort toward recommendations of specific programs for a child rather than a general type of classification of care, such as an institution or a foster family. Moreover, the data base used for the model was derived from the written intake information obtained from the facility that accepted the child for care.

This approach would not have been workable unless the authors assumed that (1) there must be patterns to the decisions about admissions and (2) such patterns must be distinctive for particular institutions or programs. In other words, it was assumed that, for the majority of cases, the program administrator would make a similar decision when confronted with another child with similar characteristics and needs. It was anticipated that the populations of children served by different providers of care would overlap and that there would be multiple reasonable alternative placements for some children. However, the success of the modeling effort required that the groups of children admitted to particular programs differed more from each other than individual children in the same group did from one another.

METHODOLOGY

During the first 3½ years of the study (January 1981–May 1984), data were collected using a purposive sample of 2,799 cases from 59 programs for children. These programs include 5 adoption or foster care programs, 10 group homes, 11 basic child care institutions, 27 residential treatment centers, 2 state hospital inpatient programs, 3 state correctional facilities, and 1 county juvenile probation program. The programs represented in the data base reflect the range of placement alternatives available for children in Texas and serve the placement needs of state agencies and the network of care providers that support the research effort.[11] Because of the limitation of purposive sampling, any model produced is a function of the programs included and cannot be generalized to programs not included in the model-building effort.

The 59 programs or institutions now included in the study's data base reflect the present state of the researchers' sample—not a predesigned target for the research project. The data base will be continuously expanded to include more programs and will be updated regularly to reflect current admissions to the programs. Fifty-nine programs are, however, a large enough set of alternatives to include the spectrum of choices faced by many practitioners when they seek placement for a child.

The data collected to describe each of the 2,799 children included 246 items related to demographic descriptors; conservatorship; legal status; health factors; characteristics of the mother and father; items about abuse, neglect, family conflict, or violence; descriptors of the child's emotional status and behavior; previous efforts in therapy, evaluation, and placement; and school performance, behavior, and attendance. Items were selected for inclusion based on a review of the variables incorporated in previous studies and a pretest study of seven facilities.[12]

Three professionally trained case readers reviewed the intake material in each child's case record and entered it on a questionnaire form. Records were read literally, with a minimum of interpretation by the case readers. A variable was not assumed to apply to a case unless it was clearly stated or implied in the written material. Periodic duplicate reading and discussion of materials was done to enhance reliabilility.

In addition to incorporating the materials in the case records, the study asked the institutional administrators or their designees to judge the benefit each child received from the placement. These respondents categorized the benefit as high, moderate, or low, and these categories were operationally defined as the degree of willingness to accept a similar child into the program in the future.

Confidentiality was preserved by assigning each child an identification number and by leaving the only cross-reference to a child's identity with the institutional administrator. Data from the questionnaire were entered directly into the study's data base, using an interactive computer program designed to minimize errors during data entry.

As the research progressed, some data elements from the initial list of variables were combined into logical composites if the original item occurred rarely; for example, a variety of physical ailments were combined into a single variable called health problems. In addition, new variables were formed as composites of original variables; for example, the number of previous placements was entered into the data base as the sum of the individual placements in various types of programs. After all the transformations were completed, the data set for each case consisted of 133 descriptors in addition to codes for case identification, institution identification, and benefit estimate. These 133 variables provided the data for the statistical analysis.

DISCRIMINANT ANALYSIS

Discriminant analysis is a statistical technique that allows the researcher to study the differences between two or more groups of objects using several variables simultaneously. In addition to helping analyze the differences between groups, it provides a means for classifying, or assigning, an individual case into the group it most closely resembles, even if the case was not included in the sample used to develop the discriminant model.[13] The usefulness of the discriminant analysis procedure for this problem was demonstrated in an earlier study by the authors and in similar studies.[14]

The underlying assumptions of discriminant analysis require that the known grouping of cases on a nominal scale variable be mutually exclusive. The predictor or discriminating variables to be incorporated into the discriminant functions must be interval scale, like the multiple-regression equations that they closely resemble. In this study, the groupings that represented placement in a specific institution were the nominal variables, and the variables describing each case were either interval or dichotomous variables.

Discriminant analysis also assumes that each group is drawn from a population that has a multivariate normal distribution and that the population covariance matrices are homogeneous across groups. If the assumption of multivariate normality cannot be supported, as it cannot for a data set with many dichotomous variables, the computed probabilities are approximations and should be interpreted with caution.[15] Also, if, as in this study, the dispersion matrices are not homogeneous, the classification procedure uses individual group covariance matrices instead of the pooled covariance matrix.[16]

Reasonable evidence supports the value of discriminant analysis despite violations of statistical assumptions like those just described.[17] Moreover, the ability of a mathematical model to predict well—the percentage of correct classifications—is the best guide for evaluating it. If this percentage is high, violations of the statistical assumptions do little harm that is of practical consequence.

Because a discriminant model based on all 133 variables was computationally cumbersome and did not necessarily produce greater accuracy, the authors used the stepwise variable selection procedure available in the Statistical Package for the Social Sciences (SPSS) to determine how many variables should be included in the model.[18] Through this process, variables were ranked in order of their statistical contribution to discrimination between the groups, as measured by the Wilkes Lamda statistic.[19] The number of correct predictions—classification of cases based on the discriminant functions in the model versus known classification—were counted for SPSS outputs, based on increasingly larger sets of variables, in increments of 5 (5, 10, 15, and 20 variables, and so on). Although additional variables could meet the statistical criteria for entry into the solution, the number of correct predictions peaked at 30 variables. Once the peak number of correct predictions was determined, subsequent modeling efforts incorporated only the top 30 discriminating variables derived from the SPSS stepwise selection procedure. The left column of Table 1 shows the 30 variables that were the best discriminators for the 59 programs included in the modeling effort.

ACCURACY OF THE MODEL

An important consideration in developing a placement-planning tool or any predictive tool is calculation of the model's accuracy rate. For a discriminant analysis model, especially one that violates underlying statistical assumptions, the best measures of the usefulness or effectiveness of the tool are measures of the rate of coincidence between the model's predicted classifications and known classifications.[20]

SPSS provides a summary of classifications that indicates, both for individual groups and the sample as a whole, what percentage of predicted classifications coincided with known classifications. The 30-variable model of the 59 residential programs studied had an accuracy rate of 59 percent for the classification of the 2,799 cases in the sample. Without addressing yet the issue of whether this rate is acceptable, it must be pointed out that the number is likely to be an overestimate of the actual effectiveness of the model because the cases classified are the same ones used in deriving the discriminant functions.[21]

A holdout or jackknife technique in which the functions are developed on one part of the sample and evaluated on the remaining part would provide a more accurate estimate of the predictive accuracy of the discriminant functions, but such techniques are not feasible in studies that, like this one, have a small number of cases in each group.[22] The technique recommended for use in the case of small groups is a one-at-a-time holdout method, which consists of holding out one case from each discriminant analysis and classifying that case on the basis of the calculated functions.[23] The procedure can be applied to every case in the sample or to a substantial proportion, and the resulting accuracy rate can be used as the basis for estimating the model's overall effectiveness.

Classifications based on the Lachenbruch holdout method were computed for half the 2,799 cases in the study. The cases classified were randomly selected and stratified by institution to assure adequate representation from each facility. The overall rate of coincidence between the known and the predicted placements dropped from 59 percent to 31 percent.

It is still unclear whether a figure such as 31 percent constitutes an acceptable rate of accuracy for a model composed of 59 groups known to vary in their relative dispersion and to include populations that overlap in their potential membership. Although the literature provides precedents for models composed of 2 to 7 groups, the authors found no comparable statistics on acceptable error rates for models with as many groups as are contained in this model.

This dilemma was addressed by asking whether the model would be regarded as effective if either its first- or second-ranked recommendations were to match a child's actual placement. The problem with this approach is knowing how far to extend the list of recommendations considered before counting the number of times a program included on the list matched a child's known placement. Arbitrarily, the cutoff point was drawn at 10 out of 59 institutions.

Table 1 shows the accuracy rate achieved by the model for each increment in the number of institutions considered when looking for a match. If an exact match of the child's placement with the model's first-ranked recommendation is required, the model's accuracy rate is 31 percent. If either of the first two highest-ranked recommendations can be counted as a match, the accuracy rate increases to 43 percent. When correspondence of any of the model's top five recommendations with the child's placement is counted as a match, the model's accuracy rate is 63 percent.

TABLE 1. The Model's Accuracy Rate When Increasing Numbers of Recommendations Are Considered

Number of Recommendations Considered	Percentage of Known Placements that Match One of the Model's Recommendations
1	31
2	43
3	51
4	58
5	63
6	69
7	73
8	76
9	78
10	80

Up to 10 institutions were included in counting the number of matches with actual placements for two reasons. First, the model often recommended placement in programs that offer services similar to those offered by the program in which the child was placed. Second, reviews by local child placement specialists repeatedly affirmed the appropriateness of the model's recommendations. That is, the model's recommendations were reasonable, as judged by both the placement specialists' knowledge of admissions practices and by the reactions of admissions specialists at various child-caring programs when they reviewed the children referred by the model.

RESULTS

Although this article has been referring to placement recommendations as if the model selected a single program or facility for each child from the 59 alternatives, each placement recommendation consists of a rank-ordered set of alternatives. For each case classified by the discriminant model, SPSS provides two bases for selecting these alternatives—one based on the a priori probability of a child's membership in any of the 59 programs when each is considered separately and another based on the posteriori probability of membership in the programs in the model when all are considered collectively and simultaneously. The a priori probability is the probability that a member of the predicted group would be as far from the centroid as the case being classified.[24] The interpretation frequently used to ex-

TABLE 2. Variable Lists for Models That Included All Cases

Variables in First 59-Program Model	Model with Only Child Descriptors
1. Conservator—youth council	1. Age at current placement
2. Age at current placement	2. Number of personal problems
3. Legally committed	3. Child is a male
4. Number of personal problems	4. Number of legal problems
5. Conservator—child welfare	5. Diagnosed as psychotic
6. Conservator—juvenile department	6. Child: other behavior problems
7. Child is a male	7. Disturbed but nonpsychotic
8. Conservator—family member	8. Works below grade level
9. Siblings in same placement	9. Child: other drug use
10. Child: other behavior problems	10. Highest school grade
11. Diagnosed as psychotic	11. Child: burglary
12. Disturbed but nonpsychotic	12. Child: alcohol use
13. Prior therapy: other	13. Works below capacity in school
14. Legal status—delinquent	14. Child: argues, is uncooperative
15. Child: other drug use	15. Child: poor self-esteem
16. Legal status—dependent and neglected	16. Number of peer problems
17. Ethnic, racial minority	17. Child sleep disorders
18. Prior psychological testing	18. Some degree of retardation
19. Highest school grade	19. Child: isolated or withdrawn
20. Wilderness camp placement	20. Child: lies
21. Works below grade level	21. Special educational classes
22. Mother physically ill	22. Offenses of a legal minor
23. Correctional facility placement	23. Child: blames others for problems
24. Number of emergency placements	24. Easily distracted, lazy in school
25. Family lacks economic resources	25. Offenses against property
26. Number of legal problems	26. Child: attacked persons
27. Works below capacity in school	27. Child: seeks younger friends
28. Emotional abuse	28. Child: marijuana use
29. Child: poor self-esteem	29. Child: suicide threats
30. Child: argues, is uncooperative	30. Child: runaway

plain the a priori probability to caseworkers is that it is an indicator of the similarity of a particular child to the group of children studied at each placement program; higher numbers represent stronger similarity, similar to the "Centour Score" concept developed by Tiedeman and Rulon.[25]

The posteriori probability is the Bayesian posterior probability, which indicates which group the case belongs to, given the pattern of resemblance to individual groups.[26] The posteriori probability assumes that the sample of included groups represents the universe of possibilities.[27] For caseworkers, then, it represents a forced ranking among the institutions included in the model; even though a child's similarity to the sample of children previously admitted to an individual program is low, the model still produces a rank-ordered list of the 10 programs most likely to admit that child.

Because factors apart from those considered in the model, such as available openings and funds, impinge on placement decisions, providing users with only 1 or 2 recommendations would often be inadequate information. A more reasonable number of recommendations would be 10, to offset the possibility of a lack of vacancies in particular facilities or restrictions on the use or amount of available funds. By developing a new format for these outputs, rather than using SPSS's format, the researchers were able to include the names of the facilities recommended and other useful information. A sample of this format is shown in Table 5, which will be discussed later.

FROM ONE MODEL TO FOUR

As discussed so far, the list of discriminating variables produced by the model is dominated by variables related to a child's conservatorship and legal status, as shown in the lefthand column of Table 2. Such variables reflect program design and funding resources; programs often serve an identifiable group of children placed by a particular state agency, which can pay a fixed rate for their care. In short, in determining where a child will be placed, variables related to the child-placement system are often as important, if not more important, than the child's behavioral problems or other characteristics.

Aware that these variables might be surrogates for factors associated primarily with the child placement system and secondarily as descriptors of children, the authors decided to investigate where children would be placed if only their behaviors, problems, and characteristics were taken into account. To examine this question, an SPSS stepwise discriminant analysis was conducted excluding the following factors: the child's conservator, legal status, and descriptors of the child's family. The resulting model focused exclusively on the child and identified the more important or useful descriptors of a child who needed placement. The results are shown in the righthand column of Table 2. As might be anticipated, the list begins with those characteristics of the child that also were selected by the first model from the full variable set; additional descriptors of the child's behaviors were included as well.

It is not surprising to see that the placements recommended by the two models can be different. Contrasting the recommendations produced by each model lends insight into the roles played by the variables of conservator and of legal status and, to a lesser degree, of problems in the child's family. The recommendations produced by the second model suggest which programs seem

TABLE 3. Four-Model Typology Formed by Including Different Combinations of Cases and Variables

Variables Included	Cases Included: All Cases in All Benefit Groups (High, Medium, Low)	Cases Included: All Cases Except Low-Benefit Group
All variables from admission records	Model 1	Model 2
Selected variables describing child	Model 3	Model 4

capable of working with the child's presenting behaviors regardless of the child's legal status.

As discussed earlier, the study collected subjective judgments by asking administrators or their designees to rate each child's degree of benefit from placement as high, moderate, or low. Models were developed, then, from the information describing only children judged as achieving moderate or high benefit. This led to the four-model typology shown in Table 3. Models 1 and 3 are regarded as initial screening models; they predict how similar a child is to others that the institution has accepted in the past. Models 2 and 4 refine these comparisons by depicting a child's similarity to children who, in the opinion of the administrator or staff of the facility, benefited from the placement in the past.

Table 4 shows the list of discriminating variables after low-benefit cases were excluded. Comparing the recommendations produced for the same child by Model 1 as opposed to Model 2 or by Model 3 versus Model 4 lends insight not only into the child's similarity to those previously admitted to a program (Models 1 and 3) but into the child's similarity to those who have benefited from the program (Models 2 and 4).

The study included no method for comparing the administrators' criteria for benefit, either in terms of validity or reliability; it assumed that administrators and their staffs are more likely to accept into their program children similar to those they judged to have benefited from their programs in the past. Likewise, they are likely to avoid children who are like those they thought did not receive much help from the placement.

TABLE 4. Variable Lists for Models That Excluded Low-Benefit Cases

Model with All Available Variables	Model Only with Child Descriptors
1. Conservator—youth council	1. Age at current placement
2. Age at current placement	2. Number of personal problems
3. Legally committed	3. Number of legal problems
4. Number of personal problems	4. Child is a male
5. Conservator—child welfare	5. Child: other behavior problems
6. Conservator—juvenile department	6. Disturbed but nonpsychotic
7. Child is a male	7. Diagnosed as psychotic
8. Conservator—family member	8. Works below grade level
9. Siblings in same placement	9. Highest school grade
10. Child: other behavior problems	10. Child: burglary
11. Legal status—delinquent	11. Child: other drug use
12. Distrubed but nonpsychotic	12. Child: alcohol use
13. Diagnosed as psychotic	13. Child: argues, is uncooperative
14. Prior therapy: other	14. Some degree of retardation
15. Child: other drug use	15. Child: poor self-esteem
16. Legal status—dependent and neglected	16. Number of peer problems
17. Ethnic, racial minority	17. Works below capacity in school
18. Highest school grade	18. Child: sleep disorders
19. Prior psychological testing	19. Child: isolated or withdrawn
20. Mother physically ill	20. Child: lies
21. Number of legal problems	21. Offenses of a legal minor
22. Family lacks economic resources	22. Special educational classes
23. Correctional facility placement	23. Easily distracted, lazy in school
24. Works below grade level	24. Child: blames others for problems
25. Number of emergency placements	25. Child: attacked persons
26. Wilderness camp placement	26. Offenses against property
27. Child: poor self-esteem	27. Child: seeks younger friends
28. Child: argues, is uncooperative	28. Speech or language handicap
29. Some degree of retardation	29. Number of school problems
30. Emotional abuse	30. Child: marijuana use

DISCUSSION

According to statistical indicators of accuracy and the judgments of child placement practitioners, discriminant analysis techniques provide a statistical base for developing models of decision making in child care that produce effective, but not perfect, recommendations. The authors subsequently developed computer software to enable child placement workers to consult models for placement recommendations. The software was field tested during 1984 by child welfare caseworkers in 3 of the 10 administrative regions in Texas and by child placement staff at the statewide reception center for juvenile delinquents; statewide training will be conducted this year. Workers access the placement models by entering case data on a computer terminal and receive immediate screen displays of the placement recommendations for the case entered. Table 5 shows a sample display of recommendations.

The results of the present study suggest that similar research and statistical procedures could be used to analyze other decisions in the human services and other fields, including decisions about removing an abused child from his or her home, judgments about the best time to return a foster child home, the selection of living arrangements for elderly persons, and decisions about which prisoners to parole. Although these examples illustrate the application of modeling techniques to decisions about individual clients, computer simulation also provides a powerful tool for assessing the probable consequences of alternative policy options for groups of clients. The modeling process makes it

TABLE 5. Sample Placement Recommendations for Model 1.

Institution or Program Recommended for This Child	Similarity to This Group Only	Forced Ranking among all Groups
Training school 1	.6814	.4117
Rural Boys' Ranch	.4640	.3916
Group home 1	.1900	.1030
Group home 2	.0431	.0693
Group home 3	.8293	.0193
Treatment center 1	.9168	.0045
Halfway house	.0609	.0003
Training school 2	.0049	.0002
Training school 3	.0002	.0000
Group home 4	.0000	.0000

possible to simulate, for example, the impact of eliminating certain programs from the spectrum of services. Analyses of this type have been applied to the Texas child care system. One simulated the consequences of a key program's potential bankruptcy and identified the cost of placing the children elsewhere. Another simulated the feasibility of shifting a portion of those enrolled in the state's training schools to community-based programs.

The present study suggests that the application of computer modeling techniques to resource-allocation and case-management decisions may soon be both practical and routine. The development of distributed computer networks and the electronic storage of case files will eventually provide the infrastructure necessary to make these applications feasible. Even before such networks and data bases are developed, computer modeling techniques can help define the data elements that need to be routinely stored. Ultimately, computer modeling techniques will be used to analyze those data elements and to recommend actions on individual cases or policy questions.

NOTES AND REFERENCES

1. H. S. Maas and R. E. Engler, Jr., *Children in Need of Parents* (New York: Columbia University Press, 1959).

2. S. Briar, "Clinical Judgment in Foster Care Placement," *Child Welfare*, 42 (April 1963), pp. 161-169; E. D. Jaffee, "Correlates of Differential Placement Outcome for Dependent Children in Israel, *Social Service Review*, 41 (December 1967), pp. 390–400; Jaffee, "Computers in Child Placement Planning," *Social Work*, 24 (September 1979), pp. 380–385; M. Phillips, A. Shyne, E. Sherman, and B. Haring, *Factors Associated with Placement Decisions in Child Welfare* (New York: Child Welfare League of America, 1971); and Phillips, Haring, and Shyne, *A Model for Intake Decisions in Child Welfare* (New York: Child Welfare League of America, 1972).

3. M. F. Mayer, L. H. Richman, and E. A. Balcerzak, *Group Care of Children: Crossroads and Transitions* (New York: Child Welfare League of America, 1977).

4. A. Kadushin, "Children in Foster Families and Institutions," in H. S. Maas, ed., *Social Science Research: Reviews of Studies* (Washington, D.C.: National Association of Social Workers, 1978), p. 127.

5. B. Boehm, "An Assessment of Family Adequacy in Protective Cases," *Child Welfare*, 41 (January 1962), p. 12; E. Foy, "The Decision-Making Problem in Foster Care," *Child Welfare*, 46 (November 1967), p. 502; and R. A. Parker, *Decision in Child Care: A Study of Prediction in Fostering* (London, England: George Allen & Unwin, 1966), p. 26.

6. Jaffee, "Computers in Child Placement Planning," p. 380.

7. Ibid. pp. 381–382.

8. Ibid., p. 383.

9. Ibid., p. 384.

10. Briar, "Clinical Judgment in Foster Care Placement"; Mayer, Richman, and Balcerzak, *Group Care of Children;* and Kadushin, "Children in Foster Families and Institutions."

11. The research described in this article was begun by the Regional Network for Children—a cooperative association of private providers of child care—and the five public agencies in Texas that are responsible for placing children: the Texas Departments of Human Resources, Mental Health and Retardation, and Education; the Texas Juvenile Probation Commission; and the Texas Youth Commission.

12. A. J. Schwab, Jr., M. E. Bruce, and R. G. McRoy, "Matching Children with Placements," *Children and Youth Services Review*, 6 (Spring 1984), pp. 125–133.

13. W. R. Klecka, *Discriminant Analysis* (Beverly Hills, Calif.: Sage Publications, 1976), pp. 7–8.

14. Schwab, Bruce, and McRoy, "Matching Children with Placements"; F. Feldhusen, F. M. Aversano, and J. R. Thurston, "Prediction of Youth Contacts with Law Enforcement Agencies," *Criminal Justice and Behavior*, 3 (September 1976), pp. 235–253; D. E. Brookhart, J. B. Ruark, and D. E. Scoven, "A Strategy for the Prediction of Work Release Success," *Criminal Justice and Behavior*, 3 (December 1976), pp. 321-334; and S. Goodwill, "A Study of Variables Which Are Associated with Successful and Unsuccessful Furloughed Prison Inmates," unpublished doctoral thesis, Utah State University, 1979.

15. Klecka, *Discriminant Analysis*, p. 10.

16. R. A. Eisenbeis, "Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics," *Journal of Finance*, 32 (June 1977), pp. 875–900; Eisenbeis and R. B. Avery, *Discriminant Analysis and Classification Procedures* (Lexington, Mass.: D.C. Heath & Co., 1972); and D. G. Morrison, "On the Interpretation of Discriminant Analysis," *Journal of Marketing Research*, 6 (May 1969), pp. 156-163.

17. Klecka, *Discriminant Analysis*, p. 62.

18. N. H. Nie et al., *Statistical Package for the Social Sciences* (New York: McGraw-Hill Book Co., 1975).

19. Klecka, *Discriminant Analysis*, pp. 52–60.

20. Ibid., p. 62.

21. Eisenbeis, "Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics."

22. Eisenbeis and Avery, *Discriminant Analysis and Classification Procedures.*

23. P.A. Lachenbruch, *Discriminant Analysis* (New York: Hafner Press, 1975).

24. Nie et al., *Statistical Package for the Social Sciences*, p. 445.

25. R. H. Lindeman, P. F. Merenda, and R. Z. Gold, *Introduction to Bivariate and Multivariate Analysis* (Glenview, Ill.: Scott, Foresman & Co., 1980), pp. 203-204.

26. Klecka, *Discriminant Analysis*, pp. 45–46.

27. M. Tatsuoka, *Multivariate Analysis: Techniques for Educational and Psychological Research* (New York: John Wiley & Sons 1971), p. 230.