Computers in Human Services

ISSN: 0740-445X (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/wzch20

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To cite this article: Fiore Sicoly PhD (1989) Prediction and Decision Making in Child Welfare, Computers in Human Services, 5:3-4, 43-56, DOI: 10.1300/J407v05n03_04

To link to this article: https://doi.org/10.1300/J407v05n03_04

Prediction and Decision Making in Child Welfare

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KEYWORDS. Computer-aided Decisions, Statistical Models, Prediction, Decision Support

ABSTRACT. Use of computer-based statistical models to support decision making may reduce the subjectivity and uncertainty in this process to more acceptable levels. Multivariate procedures capture the collective experience of many workers by integrating information from a large number of variables and cases. Once a predictive model has been developed and validated, the profile of new cases can be compared to cases already on the data base. The probability of critical case events such as admission to care, occurrence of abuse, and placement breakdown can be identified. Such capabilities could also be incorporated into the development of computerized information systems. This would facilitate case planning and a more equitable and effective match between client needs and resource utilization.

The decisions made by child welfare workers have a significant impact on the lives of their clients. These decisions include whether or not a child should be removed from his home, what type of placement is most appropriate, what service should be arranged or provided, when children should be returned home, and whether parental custody should be terminated. Sometimes workers do not have the opportunity to make the decision: a parent may abandon or

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reject the child, an adolescent runaway may refuse to return home, or a judge may make the placement decision. But in many cases it is the worker who is in a position to make the decision or to make recommendations to the court. The child welfare system is therefore at risk of failing to adequately protect children on one hand or of applying measures that are too intrusive on the other.

Child welfare agencies have been slow to create, empirically validate, and systematically apply explicit criteria for decision making (Meddin, 1984). Instead, decisions are made in an environment of uncertainty heavily influenced by value judgments and personal biases. Empirical evidence from several controlled studies of decision making in child welfare has confirmed the inconsistency of professional judgment (Briar, 1962; Craft, Epley, & Clarkson, 1980; Phillips, Shyne, Sherman, & Haring, 1971; Wolock, 1982). This research demonstrates that workers assessing the same cases frequently do not arrive at the same decisions. For instance, Phillips et al. had three experienced practitioners independently review detailed intake schedules for 50 cases involving 94 children. Each of the three judges recommended for each child whether in-home service or placement in substitute care was most appropriate. The reviewers agreed among themselves on fewer than half of the 94 decisions. Even when there was agreement for a particular child, there was considerable variation in the case factors cited as influencing the decision.

The low rate of agreement achieved in these studies is disconcerting. If this result is indicative of the way child welfare workers make judgments about how to intervene with families, potential inequities may occur when similar situations are assessed and treated differently by different workers. It is important to note that the above research may not reflect the full magnitude of the problem. These controlled studies typically use standardized case material to ensure that each worker is exposed to exactly the same case information. In actual practice, workers may differ in the type of information collected as well as how it is interpreted. The operation of both factors would tend to accentuate even further the lack of consistency in the decision-making process. It should be noted, however, that inconsistent worker behavior may also reflect the influence of external factors and constraints – financial, political, or administrative – beyond the worker's control.

An accumulating body of psychological research in clinical judgment, decision making, and probability estimation has also documented the fallibility of human judgment (Arkes, 1981; Faust, 1986; Kahneman, Slovic, & Tversky, 1982; Nisbett & Ross, 1980). Impediments to accurate judgment include: the inability to recognize patterns of covariation; the influence of preconceived notions and expectancies; neglible awareness of the factors that influence our judgment; lack of search for and use of disconfirming evidence; errors due to the limitations of unaided memory for coding, storage, and retrieval of information; and underuse of base rate information.

STATISTICAL MODELS

The psychological literature also provides evidence that a computer and carefully derived statistical models can do at least as well as, and often better than, the clinician (Hedlund, Evenson, Sletten, & Cho, 1980; Meehl, 1954; Sawyer, 1966; Wiggins, 1981). Studies of bootstrapping show that general linear models, even those that are suboptimal, are powerful enough to reproduce and surpass most of the judgments and decisions made by professionals (Camerer, 1981; Dawes, 1979; Goldberg, 1970). Sawyer reviewed 45 studies (involving 75 separate comparisons) related to the clinical-statistical controversy. In 47 comparisons the clinical and statistical methods were approximately equal; in the other 28 comparisons, statistical procedures were found to be decisively better than clinical judgment. According to Sawyer, the clinician can contribute most as a valuable source of input data which then should be combined mechanically to select a decision or course of action with the highest probability of being correct. Although we may question the use of statistical models as the sole determinant of clinical decisions, given the evidence, we must also question the continued use of unaided clinical judgment as the sole source of these decisions.

The development of computer-based models has relied heavily on multivariate techniques, primarily discriminant function analysis and multiple regression. These powerful procedures are well-suited to the explanation and prediction of a variety of complex case outcomes or decisions. However, the implementation of multivariate analyses and the interpretation of results can be quite difficult. Some stages in the application of these procedures are outlined below. Detailed discussions of multivariate procedures can be found in many other sources (e.g., Afifi & Clark, 1984; Cooley & Lohnes, 1971; Kerlinger & Pedhazur, 1973; Klecka, 1980; Morrison, 1976).

The first step is to decide which case event or decision will be the focus of the analysis. For instance, studies related to child welfare have investigated the placement process, admission to care, and the incidence of abuse. The formation of two or more comparison groups is possible by separating cases where the outcome of interest has occurred (e.g., admission to care) from cases where the outcome has not occurred. A data collection instrument must be designed that includes those case characteristics expected to be most effective in predicting group membership. The selection of relevant variables and the development of a reliable measurement process are vital prerequisites to the success of the multivariate analysis.

It is assumed here that diagnostic judgments and case disposition are strongly influenced by the characteristics of the case as perceived by the worker. In practice, decisions may also be affected by environmental factors such as resource availability, administrative requirements, funding guidelines, and political climate. Where feasible, this contextual information should also be incorporated into the computer model.

Once an appropriate instrument has been constructed, it can be used to create a computerized data base by collecting information for a sample of cases. The sample size should be large relative to the number of variables. Multiple regression or discriminant function analysis can then be used to identify the linear equation that will most clearly distinguish between the groups. For instance, a comparison of admissions to care with cases receiving in-home service would indicate the combination of child and family characteristics that is most closely related to, and predictive of, the decision to bring children into care. The proportion of variance explained by the analysis (R squared when using multiple regression) is a good indicator of the statistical model's power. Although the failure to explain a high proportion of variance may be due to the absence of consistent relationships between case factors and outcomes, such a result might also indicate deficiencies in the measurement process. If the indicators used are of low reliability or if important factors are omitted from the model, then its explanatory or predictive power will be attenuated. For example, if placement decisions are largely a function of resource availability but the model measures only factors intrinsic to the case, then results will not be optimal.

The next important step involves testing the classification or predictive accuracy of the model that is derived. Validation is frequently carried out on the same cases used for derivation. Although this method is intuitively appealing, in fact it overestimates the true accuracy rate. Ideally, the testing of classification accuracy should be done on a different group of cases. This procedure, called cross-validation, produces unbiased estimates. One option is to randomly split the original sample so that one group is used for derivation and the second group for cross-validation. When the model developed from one sample is used to classify cases in a second sample, there is often some shrinkage in the accuracy rate compared to results with the original sample. Among other things, the degree of shrinkage depends on the ratio of cases to variables – the larger the original sample the more stable the results when classifying cases in a different sample. It is important to note that the baseline for evaluating classification accuracy is not zero but the proportion of cases that would be correctly assigned by chance alone (i.e., guessing). This baseline may fall below 10% or rise above 90%. Therefore, an impressive rate of accurate prediction may sometimes be illusory if the baseline is very high.

When evaluating the effectiveness of computer-based statistical models, clinical judgment is used as the criterion for assessing accuracy. Consider a model that predicts the risk of admission to care. Accuracy is determined by comparing predictions with actual case outcomes regarding admission. The validation process assumes the statistical model to be wrong whenever the model generates results that conflict with actual case decisions. Nonetheless, it is possible that the worker's decision to admit a particular child was incorrect while the recommendation of the model was appropriate. As already discussed, assessment of the same case by different workers often leads to different conclusions. This lack of consensus constrains the potential accuracy of the computer model. A low level of predictive accuracy may therefore reflect unreliability in the criterion (i.e., clinical judgment) rather than the statistical analysis.

Following the process of cross-validation, the computerized data base can be used for classification of new cases with unknown group membership. Descriptive information about the new case is collected for the same variables maintained on the data base. It is then possible to assess the degree to which the current case resembles particular groups of cases previously served. Results may therefore be used to predict various case events such as the risk of admission to care, the risk of abuse, or the risk of placement breakdown. The higher the probabilities for a particular case the more likely that the projected outcome will actually occur. These probabilities are empirically derived, based on a synthesis of data representing the experience of many workers with many cases.

COMPUTER PREDICTION IN CHILD WELFARE

In 1979 Jaffe suggested that decision making for child placement could be incorporated into a statistical computer model. Apparently the computer model developed by Jaffe did not sufficiently correspond to actual practice to be an effective tool for child placement. He 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. Recent efforts, however, have been more promising. This section reviews several studies related to child welfare that have utilized computerized statistical models to investigate and predict a variety of case outcomes.

Argles (1983) looked at whether the duration of a child's stay in care could be predicted based on facts about the child and his family determined early in placement. A questionnaire was designed to elicit information about the age of the child at placement, handicaps, reasons for placement, frequency of parental visiting, and conditions in the foster home. The long-term-care sample comprised 239 children. The 101 children who made up the short-term-care sample had already been discharged to their parents. Argles carried out a series of multiple regression analyses which seemed to suggest that the aim of identifying predictive factors for short-and long-term care had been achieved. The regressions explained about 50% of the variance. This result indicates that certain factors which may be known before the child's placement or shortly after can be used to discriminate clearly between the long-term and short-term groups. For instance, strength of attachment as estimated by the social worker or measured more objectively by the frequency of visits invariably had a strong bearing on whether or not a child returned to his parents within a reasonable time. Classification accuracy was not investigated in this study although the proportion of variance explained indicates that the accuracy rate would have been fairly high. If, as these results suggest, the likelihood of a child entering long-term care could be estimated at initial placement, the worker could use this awareness to set realistic goals for the family concerned. In this way agencies could offer the best rehabilitative services possible for the most difficult cases knowing that failure to do so would be more costly in the long-run.

Stone and Stone (1983) carried out a study to identify reliable and objective factors that would allow the likelihood of placement breakdown or placement success to be predicted. If factors could be identified that predispose a child to failure in foster placement, perhaps both the child and the foster parent could be spared the negative consequences of such an experience. The study sample consisted of 64 children. The dependent variable of interest was the success or failure of foster placement. A questionnaire was developed comprising 63 variables grouped into four major categories: characteristics of the agency; characteristics of the natural parent and household; characteristics of the foster children; and, characteristics of the foster parent and household.

A total of 64 case records were examined. Placement breakdown occurred in 31 of these cases. Of the 63 variables, 11 were found to be significantly associated with the outcome of foster placement. The degree of contact, rapport building, and energy expended by the caseworker were most strongly related to placement success. Foster parent skills and motivation also proved to be of importance, as were characteristics of the child. In order to generate a predictive equation that would have clinical utility for caseworkers having to make placement decisions, a stepwise multiple regression was performed. This analysis accounted for approximately 30% of the variance related to outcome of placement indicating that 70% of the variability in foster home breakdowns remained unexplained. Although the accuracy of prediction was not directly determined, the results presented in the report suggest that it was between 60 and 70% (in the absence of cross-validation). Such information would provide caseworkers with a better capacity to anticipate the risk of placement breakdown so that the necessary supports could be given to the foster home.

Schwab, Bruce, and McRoy (1985) set as their objective the development of a strategy for matching children and placement alternatives. They attempted to incorporate that strategy into a computer model that would provide a rank-ordered listing of placement alternatives based on descriptive information about a particular child. A statistical analysis of placements already completed was used to identify patterns that characterized children admitted to the different residential programs in the study. The sample of 2799 children covered 59 programs including 5 adoption or foster care programs, 11 basic child care institutions, 27 residential treatment centres, and 3 state correctional facilities. The 246 data elements collected for each child included demographic information, legal status, health factors, parent characteristics, child's behavior and school performance, and previous intervention efforts.

Three trained case readers reviewed the intake material in each child's record and entered it on a questionnaire form. Some data elements in the original list of variables were combined into composites so that the 246 variables were transformed into 133 variables. In order to relate the child's information (133 variables) to placement decisions (59 programs), discriminant analysis was used. In this way individual cases could be classified into groups they most closely resembled. Initial analyses used all 133 variables. Modeling efforts retained only the top 30 variables derived from the selection process since the number of correct predictions did not increase if more variables were added into the analysis. When the cases classified were the same cases used in deriving the discriminant functions, the accuracy rate was 59%. This value dropped to 31% following cross-validation. If correspondence of any of the model's top 3 or 5 recommendations were counted as a match the accuracy rate increased to 51% and 63% respectively.

Using this model not only was it possible to compare a child's similarity to those previously admitted to the program but also to those who were judged by administrators to have benefited most from the program. According to the authors, reviews by local child placement specialists repeatedly affirmed the appropriateness of the model's recommendations. However, it was not explained how these comparisons were made or exactly how often the recommendations were judged to be appropriate.

Johnson and L'Esperance (1984) investigated how well the recurrence of abuse could be predicted by analysing the relationship between repeated abuse and case characteristics. The data collection instrument comprised 105 variables including factors associated with the parents (e.g., lack of parenting skill, substance abuse, poor self-image), factors associated with the child (e.g., age, level of development), and factors associated with the situational context of abuse (e.g., inadequate income and housing, lack of social supports).

The study sample included 120 cases of physical abuse selected from the files of a public social service agency. Of this total, 55 were cases referred for an initial incident of physical abuse in which a subsequent incident involving the same child or another child in the family had been reported within two years of the initial referral. The data collection instrument was completed using case record information that had been obtained within 90 days of initial opening and prior to recurrence of abuse. After data collection, the total case sample was randomly divided into two groups consisting of 81 and 39 cases. The researchers chose variables to be used in constructing the model that had the highest correlation with repeated abuse. In order to construct the model, the recurrence and nonrecurrence cases in group 1 were compared on variables in the predictor set using discriminant analysis. Classification functions derived from this analysis were applied to cases in the validation sample (group 2). The canonical correlation for the discriminant function was .54. The combination of five variables in the model predicted the recurrence of abuse in the validation sample with 74% accuracy compared to a rate of 50% that would be expected by chance. It is noteworthy that when the researchers looked at the relationship between recurrence of abuse and amount of effort devoted by workers to individual cases, there was no correlation. Apparently workers did not make the best use of case characteristics to identify potentially serious cases or pay greater attention to these cases before further incidents of abuse took place. These findings clearly have implications for the allocation of resources and efficient administration of programs. The computer models provide a basis for shifting resources to cases that are at greatest risk, a change that would be expected to lead to a reduction in the rate of recurrent abuse.

CONCLUSION

There will always be a high degree of individual discretion in child welfare decisions as well as financial, administrative, and political factors that constrain the worker's freedom and flexibility. However, several authors have suggested that the subjectivity and bias that may enter into worker judgments can be reduced to more acceptable levels by moving more rapidly towards the adoption of structured models of decision making (Stein & Rzepnicki, 1983; Wolock, 1982). The above studies represent some of the pioneering efforts in child welfare to develop computer models of decision making using multivariate techniques. The studies reviewed in this paper explained between 25% and 50% of the variance in group membership. This leaves considerable room for improvement since up to 75% of the variation in case outcomes remains unexplained.

One factor that certainly reduced the ability of these procedures to generate optimal predictions is the use of case records as the major source of information. The completeness, quality, and level of reliability of these records are questionable. The use of standardized measures in the context of a prospective study (instead of retrospective) would surely enhance the power of the multivariate analysis. Robins and Helzer (1986) review evidence that clinicians often omit collecting data even on topics that they believe to be essential in making a diagnosis. A standardized data collection process ensures that premature closure does not occur, and increases reliability by making uniform the amount and type of information obtained for every case. Although some standardized measures have begun to appear in the literature (e.g., Magura & Moses, 1986), this continues to be an area of child welfare where substantially more development is required.

Another possible limitation of the above studies was the method used to reduce the number of variables entered into the multivariate analysis. Although the data collection instruments encompassed a large number of variables, the majority were dropped during the analytic process leaving only a small subset (e.g., Stone & Stone; Johnson & L'Esperance). In these situations, the creation of composites might have improved the strength of the predictive equations. Finally, it should be noted that studies have not always included a cross validation phase thereby leaving in doubt the degree of classification accuracy. Validation is essential if the statistical models are to be used in supporting the decision making process.

Computer-based statistical models have the ability to capture relationships in a concise, efficient, and reliable manner while avoiding many of the biases that may undermine clinical judgment. A major strength of multivariate procedures is their ability to summarize, in a single index, information covering a large number of variables for hundreds of cases served by many different workers. Once a predictive model has been developed and validated, it is possible to classify new cases by comparing their profile with cases already on the data base. The analysis generates probabilities showing the degree of similarity between the new case and other cases on the computer file taking into account all of the input variables. This methodology can be used to predict the risk or likelihood of a wide variety of case outcomes. Caseworkers could use this awareness to plan the type and intensity of services needed, to determine the need for placement, to decide what placement type is most appropriate, to plan the termination of services, and to anticipate treatment success. This would enhance equity in the decision-making process and achieve a more effective match between client needs and resource utilization.

It should be emphasized that such statistical models would not supersede the worker's authority and responsibility for making decisions. They would function as a support to front-line staff by providing a form of instantaneous consultation with their peers (Clark, Miller, & Pruger, 1980). In fact, the statistical model that is developed simply represents the collective expertise of many workers and their experience with many cases. The process can be thought of as a computerized case conference that draws upon a vast, accumulated pool of knowledge.

Multivariate models represent only one option for the development of computerized supports to decision making. Another technology that has generated considerable excitement is expert systems. In a separate paper (Sicoly, 1988), the author compares these two methodologies and recommends an integrated approach that retains the unique strengths of each. Multivariate procedures would be applied to a data base of case information in order to generate rules that could then form the foundation of an expert system. The major contribution of the expert system is the use of natural language and explanation facilities to make the decision support process more intelligible and accountable to the user.

The availability of computer technology and powerful multivariate procedures now makes it possible to achieve more equitable and effective decisions related to case management and resource allocation in child welfare. Such capabilities could be incorporated into the development of agency information systems for the purpose of quality assurance and to support case planning at the front line of service delivery. This would respond to a common criticism (Boyd, Hylton, & Price, 1978; Geiss, 1983; Nutter, 1983) that information systems focus on routine administrative tasks, taking data from workers but offering little in return. As yet, few computer-based models using multivariate procedures have been integrated into child welfare services. Schwab, Bruce, and McRoy (1986) report the implementation, in five pilot projects, of a statistical model as a support for making decisions about child placement. Finch, Fanshel, and Grundy (1986) describe a computerized data base for tracking children in foster care, and the use of multiple regression with a variety of predictors in accounting for the discharge of children from care.

Although computerized statistical models have the potential for achieving high levels of performance, professionals continue to view them with skepticism or as an attempt to undermine their authority and autonomy. Such systems will have to demonstrate that timely information can be produced that leads to improved clinical service at a minimum cost to the user. The diffusion of this technology will accelerate as applications become more intelligible to practitioners and more responsive to their needs.

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