Using classification and regression trees (CART) to support worker decision making

Michelle A. Johnson, C. Hendricks Brown, and Susan J. Wells

Several approaches can be taken to predict case membership in the classes of a dependent variable. Classification and regression trees (CART) analysis has been cited repeatedly as a powerful nonparametric approach in fields where classification or prediction are of concern. To test CART's utility in a social work setting, the authors conducted a secondary analysis of data collected in a national study of child protective services screening practices to identify factors involved with worker decisions to investigate child maltreatment reports. The CART analysis revealed complex interaction effects previously unobserved in the logistic regression. Comparisons of CART with traditional statistical approaches and other tree-based programs are presented.

Key words: **classification and regression trees; decision trees; decision making; screening; child protective services**

Michelle A. Johnson, MSW, *is planner, Child Welfare Services Branch, Social Services Devision, Department of Human Services, 810 Richards Street, Suite 400, Honolulu, HI 96813; e-mail: mjohnson2@dhs.state.hi.us.* ***C. Hendricks Brown, PhD,*** *is professor, College of Public Health, University of South Florida, Tampa.* ***Susan J. Wells, MSW, PhD,*** *is Gamble-Skogmo Professor in Child Welfare and Youth Policy, School of Social Work, University of Minnesota, St. Paul.*

Depending on the research question, the basic purpose of a classification study is either to produce an accurate classifier or to uncover the predictive structure of the phenomenon under consideration (Breiman, Friedman, Olshen, & Stone, 1984). For most social work professionals, both objectives are of interest; for example, to target resources, a program planner must be able to identify groups of clients that are likely to benefit from a specific approach and to understand the factors that predict the likelihood of success given the client's presenting conditions. Similarly, when a social worker recommends care alternatives, prediction of outcome given the client's condition, available resources, and the factors expected to influence rehabilitation are necessary to appropriately assist the client and family in their decision making. Yet, many social work professionals are faced with complex decision problems without the benefit of a set of rules to organize data. In these situations, most decision makers tend to polarize around only a few variables, potentially missing important aspects of a problem.

Although a variety of traditional statistical approaches can be used to predict the classification of cases from complex data sets, classification and regression trees (CART) analysis (Breiman et al., 1984) has been cited repeatedly as a powerful nonparametric approach in applied fields where classification or prediction are of concern, such as medicine (for example, Goldman et al., 1998; Mair, Smidt, Lechleitner, Dienstl, & Puschendorf, 1998; Thomssen et al., 1998) and mental health (Barnes, Welte, & Dintcheff, 1991; Boerstler & de Figueiredo, 1991; Craig, Siegel, Hopper, Lin, & Sartorius, 1997). For example, in a study of low-income psychiatric patients, Boerstler and de

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Figueiredo found the client's discharge from inpatient treatment at the most recent admission to psychiatric treatment to be "the most consistent, most powerful, and the only necessary predictor of high use of outpatient psychiatric services" (p.32); an important implication for program administrators. Mair et al. (1995) used CART to develop an algorithm for use in emergency room settings for the early diagnosis of heart attack based on clinical symptoms, ECG, and other myocardial measures from 114 patients. The method's ability to predict a diagnosis was as high as that of other statistical methods; however, CART's graphical features, essential for use in clinical training and practice, were cited as a primary advantage over other methods.

To demonstrate CART's potential for use in social work settings, this article presents the CART technique, its utility in identifying factors involved with decisions to investigate reports of child maltreatment, and comparisons of CART with traditional statistical approaches and other tree-based software programs.

BACKGROUND

In response to the growing discrepancy between the number of reports made to child protective services (CPS) and the number of reports investigated, the Children's Bureau funded an on-site study of CPS screening practices in 12 communities from five states to illustrate worker decision-making practices at intake (Wells, Fluke, Downing, & Brown, 1989). Sites in each state were selected on the basis of their geographic diversity, average receipt of at least 100 child maltreatment reports per month, and willingness to participate. The 12 sites were located in urban, suburban, and rural areas in southern, western, and northern states (Table 1). Sociodemographic data collected for each site reveals the variety of communities participating in the study. For example, Site A was an urban, relatively poor area with a large population of color. Site C had roughly the same population but was suburban with a population that was 90 percent white. Site I was very poor and rural with a mainly white population. Of the five states selected, two had formalized screening practices and two had state laws and policies that did not allow for screening. The fifth state did not have laws that allowed for screening, but had at least one site with local informal screening policies.

Intake workers at the 12 sites recorded descriptive child and family information for all reports made to CPS units concerning the welfare of a child throughout specified one-month study periods. Information collected included source of report, number of previous reports, type of maltreatment and other problems reported, injuries reported, identity of reported perpetrator, type of household reported, report disposition and reasons for disposition, and type of response required. The types of allegations made (N = 2,504) were quite similar to national statistics across all categories (American Association for Protecting Children, 1988), with 36 percent of allegations involving neglect, 21 percent involving physical abuse, 12 percent involving sexual abuse, 18 percent involving other maltreatment, and 14 percent involving no maltreatment. Five percent of the sample involved allegations of severe injury, 30 percent of the referrals involved children who had been reported previously, and parents in the home constituted 61 percent of the alleged perpetrators. Reports made by different sources on the same day or within one day on the same problem (that is, duplicated reports) and reports that did not meet state statutory requirements for investigation were eliminated to permit an analysis of 1,789 reports for specific allegations of maltreatment and unspecified allegations with injury. Sixty-six percent of these reports were accepted at intake and investigated, with the proportion of reports investigated by site ranging from 35 to 100 percent.

In the initial analysis, logistic regression was used to determine which case factors contributed to the decision to investigate. Single logistic analyses were first run using all category values of each variable. In situations where effect sizes were similar, little substantive difference appeared across categories, or few cases appeared in a category, variables were collapsed with consideration given to statistical significance as well as to what appeared theoretically sound based on the authors' review of the research literature. In the next step, variables were grouped into three major categories: (1) characteristics of the contact, including source of the contact, completeness of information given and recorded, site, and whether the contact was made during business hours; (2) sociodemographic characteristics of the subjects of the contact, including age of the youngest child referred,

TABLE 1—Characteristics of Study Sites Used in Classification Tree Analysis of Factors Predicting CPS Investigation

Study Sites										
A	B	C	D	E	F	G	H	I	J	K
State (n = 5)	Site (n = 12)	Reports Received (n = 1,789)	% of Reports Investigated	Site Population (nearest 100,000)	% Not White	Urbanicity	% Unemployed	Median Household Income	% of Families in Poverty	CA/N Reports Per 100 Families
1	A	140	94	200,000	>50	Urban	<10	<15,000	>10	8
	B	130	100	100,000	>10	Urban	<10	<15,000	>10	9
	C	165	61	200,000	>10	Suburban	<10	>15,000	<10	2
2	D	203	61	400,000	<10	Suburban	<10	>15,000	<10	6
	E	162	81	300,000	<10	Suburban	<10	>15,000	<10	7
3	F	122	59	200,000	<10	Urban	<10	>15,000	<10	8
	G	61	72	100,000	<10	Urban	<10	>15,000	<10	6
4	H	81	85	100,000	<10	Urban	>10	>15,000	>10	6
	I	159	94	200,000	<10	Rural	>10	<15,000	>10	6
	J	55	98	100,000	<10	Rural	>10	<15,000	>10	9
5	K	266	35	>1,000,000	<10	Urban	<10	>15,000	<10	5
	L	245	37	600,000	<10	Urban	<10	>15,000	<10	8

NOTE: Demographic data in columns E–J were derived from U.S. Census Data, 1980–86. These numbers have been rounded to preserve the anonymity of participating sites. CA/N = child abuse/neglect.

ethnicity, gender, and household composition; and (3) characteristics of the allegation, including type of maltreatment alleged, other child and family problems described, number of children alleged to have been maltreated, previous reports on the subject of the referral, previous reports on the sibling, perpetrator or parent of the alleged victim, and identity of the perpetrator.

Separate multiple logistic analyses were run in each of these three categories to identify variables or combinations of variables in predicting the screening decision, using likelihood ratio

TABLE 2—Factors Predicting CPS Investigation, Logistic Regression (N = 1,789)

Variable	Estimate	*SE*	*df*	χ^2	*p*
Site			8	317.20	<.001
C	–3.10	.30			
D	–3.00	.29			
E	–1.91	.32			
F	–3.41	.32			
G	–2.48	.39			
H	–1.59	.40			
K	–4.29	.29			
L	–4.13	.28			
A	0	—			
B	0	—			
I	0	—			
J	0	—			
Injury			2	83.69	<.001
Severe	2.14	.32			
Minor/mixed	1.16	.16			
Unknown/missing/none	0	—			
Allegation			1	46.08	<.001
Sex abuse	1.55	.23			
All other types of maltreatment	0	—			
Identity of Perpetrator			1	6.33	<.01
Any known perpetrator	.58	.23			
Perpetrator unknown	0	—			
Age			1	9.87	<.01
Under two years	.53	.17			
Two or over, missing	0	—			
Gender			1	10.54	<.001
All female children reported	–.43	.13			
All male children or mixed, unknown	0	—			
Household type			1	8.97	<.01
Any known type of household	.49	.17			
Unknown, missing	0	—			
Source of report			3	40.83	<.001
Nonperpetrating parent	–1.20	.22			
Self (victim or perpetrator)	–1.05	.36			
Friend/relative/other	–.51	.17			
Mandated reporter/anonymous/neighbor/multiple/ not recorded, unknown	0	—			

NOTE: — = not applicable.

(chi-square) tests. Because of the central role that unknown and missing data play in decision processes, items left blank or recorded as unknown were treated as valid variables. Analysis of 1,789 reports uncovered a predictive model consisting of the following variables: type of injury, type of maltreatment, perpetrator identity, age of youngest child reported, gender, and source of report (Table 2).

Controlling for all of these factors, site was generally the strongest predictor of whether or not an investigation was conducted—that is, a referral made by a mandated reporter of an injured child under two involving sexual abuse by a known perpetrator was still less likely to be the subject of an investigation in sites C, D, E, F, G, H, K, or L compared with sites A, B, I, or J. For two variables, identity of perpetrator and household type, it was important that the information was known to the worker, regardless of further details reported. Although report characteristics did make a difference, site was found to be the strongest factor predicting the decision to investigate.

METHOD

Classification and regression trees analysis (CART) (Brieman et al., 1984) was primarily used to model the decision to investigate. CART is a statistical technique used to form prediction rules for an outcome variable based on the values of predictor variables. Similar to traditional approaches such as logistic regression, CART analysis seeks accurate prediction and uses decision equations. The hierarchical nature and flexibility of CART differentiate it from traditional methods in important ways, however. CART searches systematically for all possible ways to split each predictor variable into high and low groups (for example, age greater than or less than six years) and selects the split that best separates investigated from noninvestigated cases. CART then continues to examine the best split involving all predictors for each of the two subgroups already formed (that is, below and above six years of age). The searches for best predictors continue with every split, forming a new subgroup from previous ones until homogeneity is obtained. When combined sequentially, the subgroups formed by each split are arranged in a tree formation, hence CART's name.

The primary assumption underlying the CART analyses is that, except for random variation, all other variation in a dichotomous outcome, such as the decision to investigate or not, can be explained by a model in which the probability is determined by subsetting the data based on a sequence of binary splits of independent variables. CART also assumes that given these different probabilities for each subset, all subjects' outcomes are independent of one another. Logistic regression also assumes independent outcomes. It, however, assumes a logistic shape between the probability of an outcome and a suitable linear combination of the independent variables. In contrast to logistic regression, CART allows for different predictors to come into play for each subgroup, thus allowing for complex interactions that are rarely included in logistic regression models. A second advantage of CART is that its hierarchical tree structure better mimics human decision making and is relatively easy to interpret.

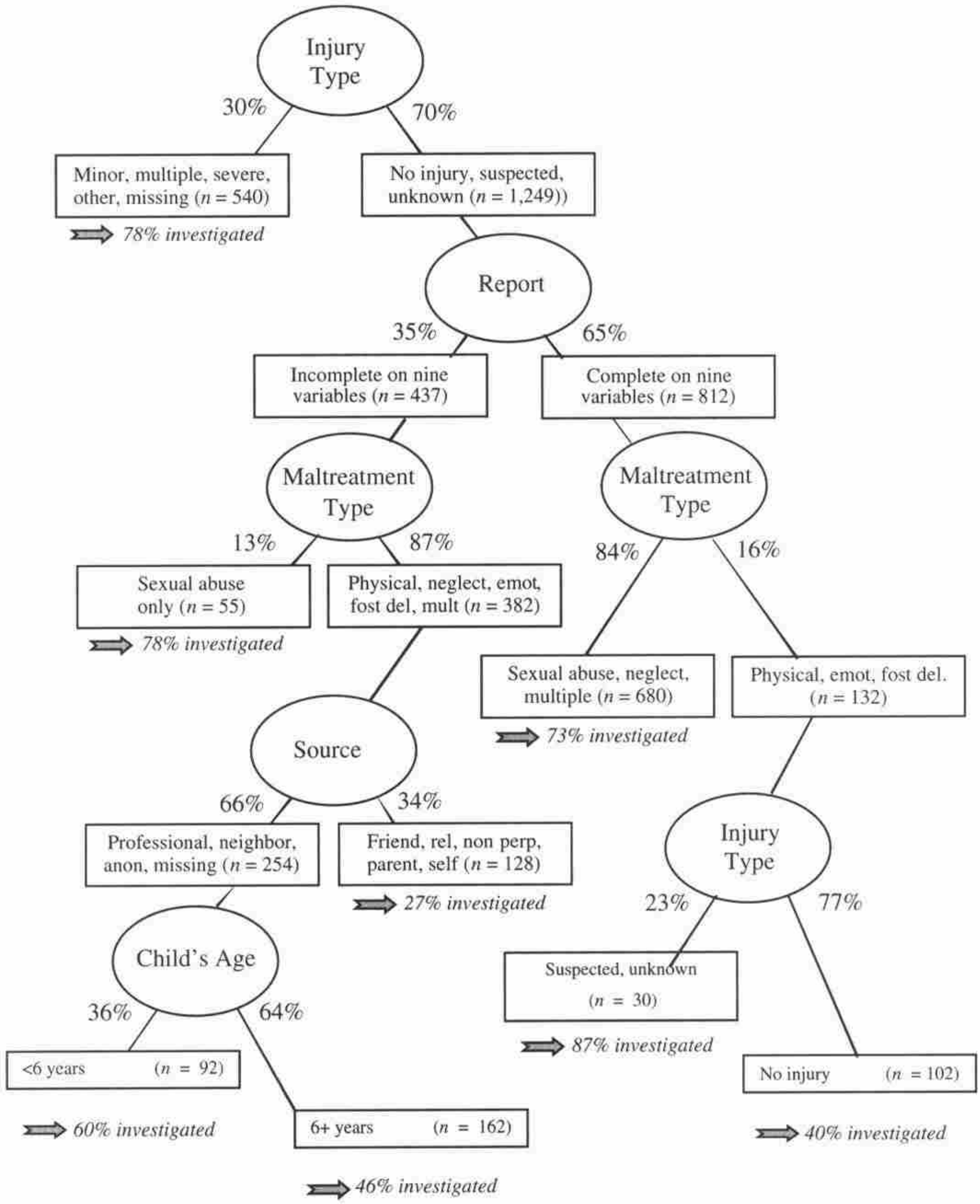
Classification trees can be computed for categorical predictors, continuous predictors, or a mix of the two types. Splits also can be computed for classification trees when continuous predictors are measured on at least an interval scale. Unlike logistic regression, the recursive approach implemented for classification trees provides for many alternative combinations of variables. For example, dozens of recursive splits are examined by CART when there are only a handful of predictor variables and two classes on the dependent variable. For logistic regression, all linear combinations of the predictors are considered, and interactions need to be entered explicitly. Using the same data, we found CART analysis yielded a better summary.

ANALYSIS

The process of computing classification trees can be characterized as involving four basic steps: (1)specifying the criteria for predictive accuracy, (2) selecting splits, (3) determining when to discontinue splitting, and (4) choosing right-sized trees. We conducted CART analysis in classification mode ($N = 1{,}789$) using variables found to be predictive of the decision to investigate as described in the initial logistic regression, with the exception of type of injury which was treated dichotomously as presence of injury in the secondary analysis. We first ran CART analysis without site identification.

In classification mode, the tree algorithm began by considering all variables simultaneously to

FIGURE 1—Factors Predicting CPS Investigation, CART Analysis (N = 1,789)



determine the best variable splits among the values and categories of all variables. Tree growth resulted as the algorithm partitioned variables by either a grouping of a variable's categories into the two most homogenous sets for categorical data or a range split of values for continuous data (that is, child's age). For example, for injury type—the first categorical variable split—one branch consisted of minor, multiple, severe, other, and missing injury (n = 540; 78 percent investigated) whereas no injury, suspected, and unknown injury formed the other branch of the tree (n = 1,249) (Figure 1).

The latter branch was then split by the second categorical variable—completeness of report or referrals missing one or fewer of the following nine variables: child's age, gender, ethnicity, type of problem, type of injury, perpetrator identity, type of household, source of referral, and existence of previous reports. For each split, numbers in parentheses indicate the number of cases satisfying the criteria specified. A continuous variable such as child's age could be split at any value within the age range specified. In this analysis, children younger than six years formed one branch of the decision tree and children six years of age and older formed the other. The process of splitting continues until a group has reached a uniform outcome or is too small to split further.

After a large tree is "grown" through repeated partitioning, a stringent cross-validation procedure is used to test the tree. Randomly selected data are sorted repeatedly down the tree to test its accuracy. Only those parts of the tree that are able to improve the correct classification rate survive the test. Best splits are determined on the basis of a misclassification error to identify the split which best predicts the outcome variable (for example, the decision to investigate). CART handles missing values on predictive variables by providing information on the split that statistically is most closely associated with the best split. Again, in this example, unknown or missing data were treated as valid variables because of the critical nature of this type of data in decision processes. CART also provides information on those splits of variables that have the next largest improvement (decrease in error) when compared with the best split, regardless of the strength of the association. With this additional information, CART permits the examination of variables that are hidden or masked when simply examining the splits in the selected trees (Boerstler & de Figueiredo, 1991).

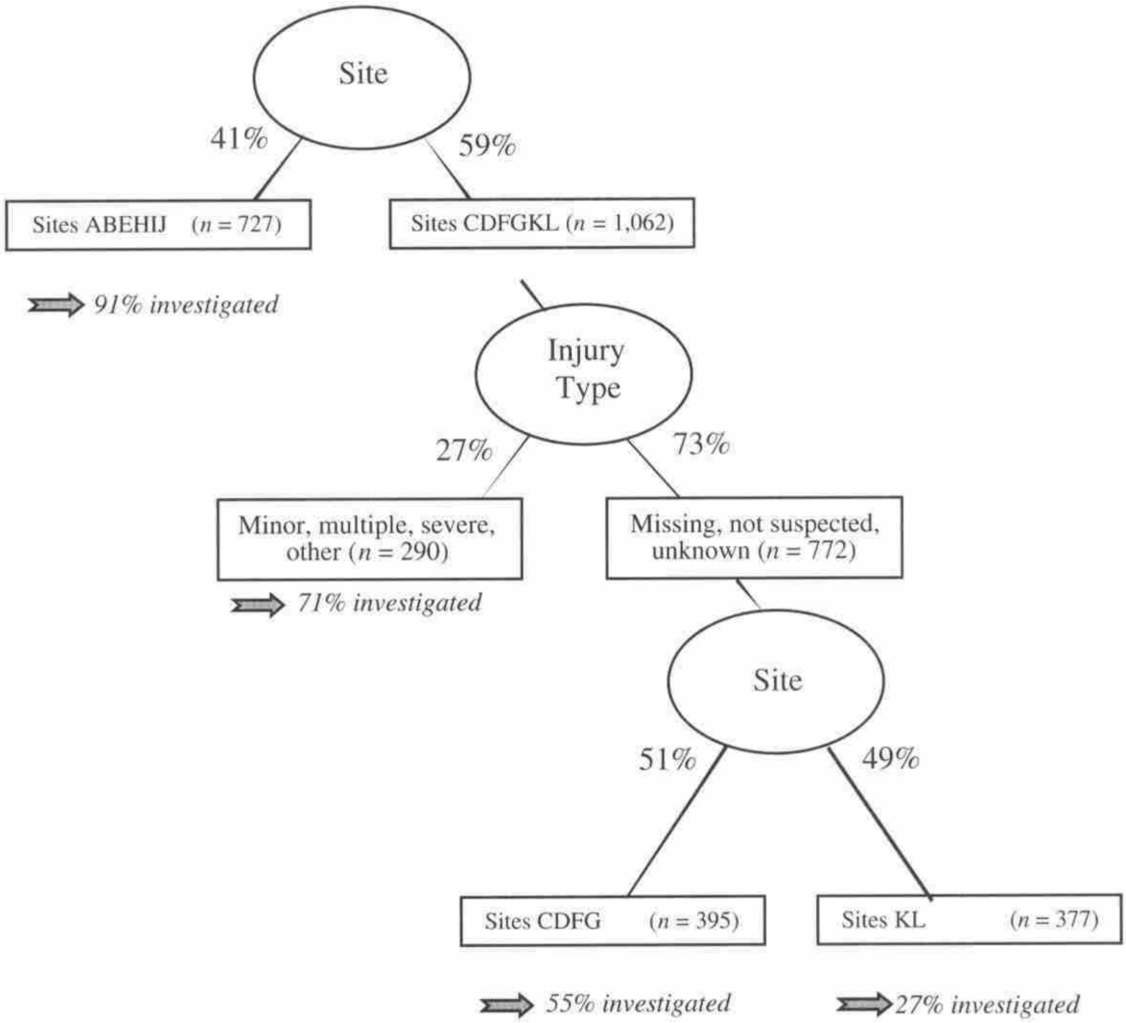
RESULTS

By better handling missing data and illustrating the interactions of multiple variables, CART provided a depth to the analysis that the logistic regression could not match. In the CART analysis depicted in Figure 1, it was apparent that the rate of investigation ranged greatly depending on the membership of a case in any one of a number of subgroups, including degree of completeness of the case report, type of injury, type of maltreatment, source of report and age of youngest affected child. Overall, two-thirds of the cases were investigated. An examination of the different subgroups indicates that the investigation rate ranged from a high of 87 percent for children with suspected or unknown injuries (n = 30), to 78 percent for children with some type of injury or a report of sexual abuse, to a low of 27 percent for children with reports of nonsexual abuse reported by family or friends but with little additional information. Whenever sexual abuse was reported, there was a high degree of investigation even when the report was incomplete (n = 55). This was not true for other types of abuse, particularly those involving neglect or multiple forms of abuse. Completeness of the report was relevant primarily among those cases with no injuries or suspected injuries or where the worker noted that information on an injury was unknown (n = 1,249). Similarly, the absence of any reported injury (n = 102) was an important predictor (40 percent investigated) for cases of physical abuse and emotional abuse in which the reports were missing little or no information.

As mentioned earlier, when a report was relatively incomplete, the type of maltreatment alleged was not sexual abuse, and the source of report was a friend or relative, nonperpetrator, parent, or self (n = 128), only 27 percent of reports were investigated. However, if the reporting source was a professional, neighbor, anonymous, or missing, then the child's age was strongly related to investigation. Cases involving young children less than six years of age (mostly preschoolers) were more likely to be investigated (60 percent) compared with cases involving school-age children (46 percent). On the other hand, when the data were relatively complete (n = 812), indications of sexual abuse as well as neglect or multiple maltreatments led to a high probability of investigation (73 percent). If there was physical abuse, emotional maltreatment, or fostering delinquency, and injury was either suspected or unknown, then 87 percent were investigated, compared with 40 percent investigated when no injury was reported.

In the initial logistic regression analyses the introduction of site screening policies into the equation dominated the results: Site alone was most predictive of the decision to investigate. Backward elimination was used to test for site variations after

FIGURE 2—Site Impact on the Decision to Investigate, CART Analysis (N = 1,789)



adjusting for all other variables; here the effects on investigation rates were no less striking than the unadjusted rates. To test the significance of screening policies using CART, we next introduced site into the equation (Figure 2).

Site differences, as expected, were extremely large, from 91 percent investigated overall in one group of sites to only 27 percent of cases investigated where no injury was alleged in two sites (n = 377). Three clusters of sites emerged: A, B, E, H, I, and J, which investigated nearly all cases and the other two groups which generally investigated cases with reported injuries. Sites C, D, F, and G investigated 55 percent of the cases without reported injuries, whereas sites K and L investigated 27 percent of the cases without reported injuries.

CART analyses were conducted on a site-by-site basis to determine whether any screening models could be derived by site. These analyses were helpful in identifying site-specific variations caused by different policies, training, or staffing. Type of injury was the most important factor in identifying cases that were screened for investigation in five of the sites. However, for many of these analyses, type of injury did not reach statistical significance. Other salient factors included level of completeness of the report (the most important factor in one site) and the age of the youngest child reported (the most important factor for another site). Two sites failed to identify any factors associated with the screening decision: Nearly all reports were not investigated.

As with the use of any statistical method, great care must be exercised in interpreting findings. For identifying models that predict well, there is no substitute for a thorough understanding of the nature of the relationships between the predictor and outcome variables. Results may appear to suggest that relationships are lacking when predictors that tend to be correlated do not all appear in a tree. In some cases the expected relationships may be subsumed by other variables (Temkin, Holubkov, Machamer, Winn, & Dimken, 1995). At the same time, results may suggest relationships that appear valid at face value but require further examination. For example, in this study, initial results suggested a predictive relationship between ethnicity and the screening decision. We were able to attribute the low investigation rate to the site's stringent screening policy rather than to the demographic characteristics of the site.

DISCUSSION

In this analysis the CART methodology, based on subgroups rather than sums of linear terms, provided an unparalleled depth to the results by identifying interaction effects and relationships within the context of site. CART analyses provide a decision tree that prioritizes important report characteristics conveniently and tracks the rate of investigation in specific subgroups with ease. On the other hand, logistic regression provides a weighted combination of characteristics that, once computed, can lead to an assessment of whether a decision is made or not. It is relatively weak, however, as a tool for making substantive interpretations about how CPS workers actually come to decisions. Using kappa to measure the proportion agreement beyond chance, a better kappa was found for the logistic regression (.518) compared with that of CART (.261). The larger value for logistic regression is most likely the result of the added cross-validation step used by CART. Without this step, in which the tree is pruned up to the level where the cut points can be reliably determined, CART trees would naturally be much larger and would also obtain better kappas. In this comparison, then, the logistic regression may yield more predictive ability, whereas the CART describes more richly the actual decision making process.

A closer examination that considers the complexities of site-level factors such as demographic characteristics, available resources, screening policies, and community definitions of child abuse and neglect is necessary to further define the factors contributing to workers' decisions to investigate reports of child maltreatment. However, CART's ability to detect important interaction effects within the context of site is clearly of more value than understanding the significance of site alone. To illustrate, consider Craig et al.'s (1997) secondary CART analysis of data on more than 1,000 people assessed close to the onset of schizophrenia and followed for two years to track illness trajectory. In the initial analysis, course and outcome were found to be more favorable for subjects living in sites in developing countries than for those in developed areas. In the CART analysis, pattern of course continued to be best predicted by site and type of onset, but two developed sites also grouped with developing sites, showing better outcomes than in the remaining developed sites. Effects for some groups were modified by other predictor variables, including age, child/adolescent problems, and gender. CART's ability to detect complex interactions between variables in groupings not strictly defined by developing and developed sites allowed the authors to identify important implications for clinical practice, including the necessity of comprehensive patient examinations, the need for intensified treatment for specific groupings, and the capacity to improve clinical care by tailoring treatment to the culture and specific circumstances of the patient (Craig et al. 1997).

The flexibility and graphical nature of classification trees make them an attractive analysis option, but this is not to say that their use is recommended to the exclusion of other methods. In fact, CART has been described as the method of last resort when all other methods have failed to detect an accurate classifier (Breiman et al., 1984). When the typically more stringent theoretical and distributional assumptions of traditional methods are required, these methods may be preferable. Multilevel modeling (for example, HLM or Mln) also has proven to be a useful analysis in educational and social settings that not only takes the nested structure of data into account, but also estimates interactions across multiple levels by regressing coefficients from first level models (for example, worker) on second and third level variables (for example, site or community) to identify cross-level interactions (Kreft & de Leeuw, 1998). Had the site variable been treated as a random effect in this study it would have necessitated the use of multilevel modeling or modification of standard errors through the generalized estimating equation's "sandwich estimator." In these analyses, site locations were treated as fixed, allowing separate probabilities to be fitted to each site that differed from the others. There were no second level predictors because they were treated as fixed effects.

Other tree-based programs such as QUEST (Loh & Shih, 1997) and MedTree (Kroger & Kroger, 1996) compute binary classification trees based on univariate splits for categorical, ordered, or a mix of both types of predictor variables and also compute classification trees based on linear combination splits for interval scale predictors. MedTree uses an algorithm designed to increase the quality of the classification trees by calculating a large number of possible segments of trees instead of a single tree and recursively selects the best of these parts to form an optimal tree. Some classification tree programs, such as FACT (Fast and Accurate Classification Tree) (Loh & Vanichestakul, 1988), THAID (Theta Automatic Interaction Detection) (Morgan & Messenger, 1973) and related programs such as AID (automatic interaction detection); Morgan & Sonquist, 1963) and CHAID (chi-square automatic interaction detection) (Kass, 1980) perform multilevel splits, rather than a single or binary split when computing classification trees. Any multilevel split can be represented as a series of binary splits; therefore there is no inherent advantage to multisplit levels. In fact, with multilevel splits, predictor variables can be used for splitting only once, so the resulting classification trees may be short or lacking in depth (Loh & Shih, 1997).

A more serious problem reported is a bias in selecting variables with more levels for splits. This bias can skew the interpretation of the relative importance of the predictors in explaining responses on the dependent variable (Breiman et al., 1984). This bias is possible in any program that uses an exhaustive search for finding splits (for a discussion see Loh & Shih, 1997). Bias in variable selection can be avoided by using the discriminant-based split options. These options make use of the algorithms in QUEST (Loh & Shih) to prevent bias in variable selection. The CART style exhaustive search for univariate splits option is useful if the goal is to find splits producing the best possible classification in the learning sample, but not necessarily in independent cross-validation studies. For reliable splits, as well as computational speed, discriminant-based split options are recommended.

CONCLUSION

CART's graphical features and reported ease of use in clinical training and practice hold promise for improving service to clients and maximizing resources. Ideally, the benefits of repeated analysis of factors, combined with the indispensable knowledge of workers, clients, and communities, will lead to the construction of accurate, consistent and effective models to structure and support social work administration and practice. Furthermore, comparisons on a case-by-case basis of the predicted outcome with the standard client intervention to the actual outcome with an innovative treatment may provide the best evaluation of the innovation short of a randomized trial (Temkin et al. 1995). ■

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Peace Power for Adolescents

Strategies for a Culture of Nonviolence

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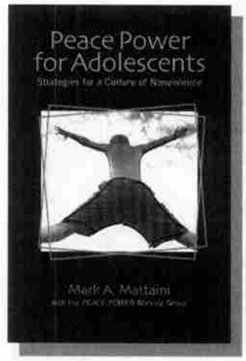

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The PEACE POWER system takes a practical approach that respects the divergent cultures and values in our society. This thoughtful method recognizes that, while the coercive and threatening aspects of modern life expose children and families to dramatically increased stresses, we can find peaceful solutions to strengthen our communities.

Special Features

- Explores the biological, experiential, and cultural roots of violence and coercive behavior
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- Identifies a core set of cultural practices that reduce violence
- Speaks to the cultural and societal forces shaping today's youth
- Offers a range of tools and activities for maintaining core practices
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