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A Classification Tree Approach to the Development of Actuarial Violence Risk Assessment Tools

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Since the 1970s, a wide body of research has suggested that the accuracy of clinical risk assessments of violence might be increased if clinicians used actuarial tools. Despite considerable progress in recent years in the development of such tools for violence risk assessment, they remain primarily research instruments, largely ignored in daily clinical practice. We argue that because most existing actuarial tools are based on a main effects regression approach, they do not adequately reflect the contingent nature of the clinical assessment processes. To enhance the use of actuarial violence risk assessment tools, we propose a classification tree rather than a main effects regression approach. In addition, we suggest that by employing two decision thresholds for identifying high- and low-risk cases—instead of the standard single threshold—the use of actuarial tools to make dichotomous risk classification decisions may be further enhanced. These claims are supported with empirical data from the MacArthur Violence Risk Assessment Study.

Violence risk assessment remains a core feature of clinical practice in a wide variety of institutional and community settings. Beginning in the late 1960s, ''dangerousness to others'' became one of the primary criteria for the involuntary inpatient hospitalization of people with mental disorders throughout the United States. In the 1970s, tort liability was imposed on psychiatrists and psychologists who negligently failed to accurately predict their patients' violence. In the 1980s, the ''dangerousness standard'' expanded to statutes authorizing involuntary outpatient treatment (Appelbaum, 1994). In the 1990s, risk assessments of violence were formally invoked

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in the Americans with Disabilities Act, which protects the employment rights of people with mental disabilities, unless those disabilities result in a person being assessed as a "direct threat" of violence to other employees or to customers (Bonnie & Monahan, 1997).

Despite the pervasiveness of violence risk assessment, the research literature on clinical prediction remains disconcerting. The most sophisticated recent study found clinicians' unstructured violence risk assessments to be only modestly more accurate than chance (Lidz, Mulvey, & Gardner, 1993). Although considerable progress has been made in recent years in structuring violence risk assessment (Borum, 1996; Quinsey, Harris, Rice, & Cormier, 1998; Douglas & Webster, 1999), actuarial tools remain largely research instruments ignored in daily clinical practice in all but a few forensic institutions.

Given the persistent finding that actuarial predictions are almost always more accurate than unstructured clinical ones (Grove & Meehl, 1996), the fact that formal violence risk assessment tools have not met with greater clinical acceptance is puzzling. We believe that this state of affairs results in part from two interrelated problems. First, virtually all existing risk assessment tools are derived from main effects linear regression models that imply that a single solution fits all persons whose violence risk is being evaluated. Clinicians, however, appear not to believe this (Gigerenzer, 1996). Second, although the overall accuracy rates of existing risk assessment tools represent a clear statistical improvement on chance, the magnitude of that improvement is not seen as clinically significant (Menzies, Webster, McMain, Staley, & Scaglione, 1994).

The research reported here bears on both these problems. Building on the work of Gardner, Lidz, Mulvey, & Shaw (1996), we propose an approach to the development of actuarial violence risk assessment tools based on the use of classification tree rather than linear regression analyses. A classification tree approach reflects an interactive and contingent model of violence, one that allows many different combinations of risk factors to classify a person as high or low risk. The particular questions to be asked in any clinical assessment grounded in this approach depend on the answers given to prior questions. Based on a sequence established by the classification tree, a first question is asked of all persons being assessed. Contingent on each person's answer to that question (or depending on the nature of the question, on the answer found in each person's records), one or another second question is posed, and so on, until each subject is classified into a high- or low-risk category. This contrasts with a regression approach, in which a common set of questions is asked of everyone being assessed and every answer is weighted to produce a score that can be used for purposes of categorization.

In addition to its tree-based character, the approach we propose makes no pretense of classifying all persons into a high or a low violence risk group. Rather than relying on the standard single threshold for distinguishing among cases, our approach to risk assessment employs two thresholds—one for identifying high-risk cases and one for identifying low-risk cases. We assume that inevitably there will be cases that fall between these two thresholds, cases for which any prediction scheme is incapable of making an adequate assessment of high or low risk (Shah, 1978). Based on current knowledge, the aggregate degree of risk presented by these intermediate cases cannot be statistically distinguished from the base rate of the sample as a whole. By focusing actuarial attention on cases at the more extreme ends of the risk continuum rather than across the entire continuum, our approach may increase predictive accuracy for the cases designated as extreme (Menzies, Webster, & Sepejak, 1985; McNiel, Sandberg, & Binder, 1998).

In short, we believe that the use of actuarial violence risk assessment tools in day-to-day clinical practice might be enhanced if (1) those tools were based on classification tree rather than main-effects regression procedures; and (2) two decision thresholds were used to arrive at a dichotomous risk classification, one to identify high-risk cases and one identify low-risk cases, leaving a residual group "unclassified."

In the remainder of this paper, we illustrate these ideas empirically by using data from the MacArthur Violence Risk Assessment (Steadman, Mulvey, Monahan, Robbins, Appelbaum, Grisso, Roth, & Silver, 1998), the largest dataset yet assembled to investigate violence risk assessment. We begin by presenting a violence prediction tool developed using a standard main-effects approach in order to show what the current leading method produces in this dataset. We then develop a tree-based violence risk assessment tool using a standard recursive partitioning software package. Both the main-effects and the classification-tree approaches are evaluated first using receiver operating characteristics (ROC) analysis and then within a two-threshold dichotomous decision–making framework. We conclude with a brief demonstration of how the idea of contingent risk assessment, when combined with a two-threshold approach to risk categorization, can be further operationalized to produce a tree-based actuarial violence risk assessment tool that may prove more potent in identifying high- and low-risk cases than other approaches currently available.

METHODS

Study Sample

The sample consisted of 939 patients recently discharged from acute psychiatric units at three hospitals (see Steadman et al., 1998, for a complete sample description). The sample size of 939 was obtained by selecting all subjects who completed one of the first two followup interviews administered during the 20-week period following hospital discharge. Subjects were assessed during the target hospitalization on a wide range of risk factors (Kraemer, Kazdin, Offord, Kessler, Jensen, & Kupfer, 1997) culled from available theories of violence and of mental disorder, from robust findings that had emerged from existing actuarial research, and from the experience of clinician/researchers. This process identified 134 risk factors from four conceptual domains: dispositional or personal factors (e.g., age), historical or developmental factors (e.g., child abuse), contextual or situational factors (e.g., social networks), and clinical or symptom factors (e.g., delusions) (Steadman, Monahan, Appelbaum, Grisso, Mulvey, Roth, Robbins, & Klassen, 1994), all of which were measured during the target hospitalization.

Collateral informants who knew of the patients' behavior in the community were also interviewed regarding risk factors and violence. Arrest and rehospitalization records provided the third source of information about the patients' behavior in the community. Violence reported by any of the three data sources—subject self-report, collateral report, or official records—was reviewed by a team of trained coders to obtain a single reconciled report of violent behavior. Violence to others was defined to include the following: acts of battery that resulted in physical injury; sexual assaults; assaultive acts that involved the use of a weapon; or threats made with a weapon in hand. Twenty weeks in the community was chosen as the time frame for this analysis because this was the period during which the prevalence of violence by discharged patients in the community was at its highest; after 20 weeks, the prevalence of violence decreased markedly (Steadman et al., 1998). We chose to focus on serious acts of violence (i.e., excluding minor assaults that did not result in injury) committed during the first 20 weeks following hospital discharge because such acts are of greatest concern to clinicians who must make assessments of violence risk.

Of the sample of 939 discharged patients included for study, 57.3% were male, the mean age was 29.9 ($SD = 6.2$), 68.7% were white, the mean number of years of education was 12.1 ($SD = 2.2$), and 32.4% had been hospitalized involuntarily. The primary project diagnosis was depression for 41.9% of the patients, 17.3% had a primary project diagnosis of schizophrenia (or schizoaffective disorder), 14.1% had a primary bipolar disorder, and 21.8% had a primary alcohol or drug use disorder.

Statistical Procedures

Logistic regression was used to develop the main effects actuarial model. The dependent measure, violence during the first 20 weeks following hospital discharge, was coded as a dichotomous outcome. In order to derive an equation that maximized explanatory power using a minimum number of statistically significant risk factors, a forward stepwise variable selection criterion was used (a comparison of results using other variable selection methods—available from the authors—showed only trivial changes in predictive accuracy). The traditional $p < 0.05$ threshold was set for the selection of risk factors, and missing values were replaced using mean substitution for continuous measures and mode substitution for categorical measures. The logistic regression equation was then used to compute predicted probabilities of violence for all 939 cases.[8] (For a complete list of bivariate correlations between each of the 134 available risk factors and the outcome measure, violence during the first 20 weeks following hospital discharge, see Monahan, Steadman, Appelbaum, Robbins, Mulvey, Silver, Roth, & Grisso, in press).

To develop the classification tree model, we used Chi-squared Automatic Interaction Detector (CHAID) software available through SPSS (SPSS, Inc., 1993). Specifically, the CHAID algorithm was used to assess the statistical significance of the bivariate association between each of the 134 eligible risk factors and the

[8]Specifically, risk factor scores were weighted by the unstandardized logistic regression coefficients, summed and then exponentiated to produce a predicted odds for each case. These predicted odds were then transformed to probability values using the formula: $p = \text{odds}/(1 + \text{odds})$.

same dichotomous outcome measure—violence in the community—until the most statistically significant value of χ^2 was identified. Once a risk factor was selected, the sample was divided (or partitioned) according the values of that risk factor. This selection procedure was then repeated for each of the sample partitions, thus further partitioning the sample. The result of the partitioning process was to identify subgroups of cases sharing risk factor attributes that also exhibited high levels of homogeneity with regard to the dichotomous outcome measure, violence.

To execute the CHAID algorithm, a number of decisions had to be made, including the setting of end-node splitting criteria, tree depth, and level of significance required for a partitioning variable to be selected (SPSS, Inc., 1993). In the analyses reported later, the partitioning process was terminated if a subgroup contained fewer than 100 cases, or, if more than 100 cases were present, the subgroup could not be partitioned into further subgroups consisting of 50 or more cases. In other words, no subgroup in the resulting classification tree was allowed to contain fewer than 50 cases. No limit was imposed on the tree depth, and the traditional $p < 0.05$ significance level was used as a necessary condition for variable selection, with missing values replaced using a method recommended by Breiman, Friedman, Olshen, and Stone (1984). The baserates of violence (i.e., percentage of violent cases) in each of the resulting sample partitions were used to derive the predicted probabilities of violence for all cases in that group.

To assess the predictive accuracy of the actuarial models produced by these methods and facilitate further comparisons of our results with other research on violence risk assessment, we used an ROC analysis, which consists of a plot of the sensitivity and 1-specificity pairs that are produced as a single decision threshold is moved from the lowest (i.e., all cases predicted violent) to the highest (i.e., no cases predicted violent) possible value. The ROC method of representing predictive accuracy is independent of the base rate of violence in the study sample (Rice & Harris, 1995; Gardner et al., 1996). The statistic used to summarize the ROC analysis is the area under the curve (AUC), which corresponds to the probability that a randomly selected violent patient will have been assessed by the risk assessment tool as higher risk than a randomly selected nonviolent patient (Swets, 1992). The AUC varies from 0.5 (i.e., accuracy is not improved over chance) to 1.00 (i.e., perfect accuracy).

RESULTS

Table 1 displays the results of the logistic regression model. As shown, 18 risk factors were selected using the forward stepwise procedure, each of which contributed significantly ($p < 0.05$) to the prediction of patient violence (see Appendix A for a description of these risk factors).[9] Two of the risk factors listed in Table

[9]When examining Table 1, it is important to note that no single risk factor can be isolated from the remaining ones as having an independent relationship with violence. For example, in Appelbaum, Robbins, & Monahan (in press), we report no bivariate relationship between delusions and violence. Yet grandiose delusions appears as the twelfth risk factor in the logistic regression model reported in Table 1. These results are not inconsistent. Only with 11 other variables maximally accounting for variation in violence does grandiose delusions come in to best account for the portion of the variation that is left. When all the variance is available, as in the bivariate test, there is no relationship.

Table 1. Main Effects Logistic Regression Model (n = 939)[a]

Risk factor	B	Odds ratio	Wald statistic (df = 1)	p Value
Psychopathy (0/1)	0.876	2.40	16.8	0.0000
Child Abuse Seriousness	0.427	1.53	15.0	0.0001
Frequency of Prior Arrests	0.286	1.33	12.5	0.0004
Father's Drug Use	0.779	2.18	11.9	0.0006
Threat/Control-Override Symptoms	−0.412	0.66	10.7	0.0011
BPRS Hostility Rating	0.127	1.14	9.8	0.0017
Prior Loss of Consciousness (0/1)	0.551	1.73	7.8	0.0053
Employed (0/1)	−0.530	0.59	6.8	0.0092
BPRS Activation Rating	−0.164	0.85	6.3	0.0122
Anger Scale: Behavioral Rating	0.038	1.04	6.3	0.0124
Involuntary Admission Status (0/1)	0.500	1.65	6.2	0.0128
Violent Fantasies: Single Target Focus (0/1)	0.628	1.87	5.8	0.0164
Grandiose Delusions (0/1)	0.826	2.28	5.7	0.0169
Impulsiveness: Non-Planning Subscale	−0.031	0.97	5.7	0.0169
Mental Health Professionals In Social Network	−1.704	0.18	5.1	0.0236
Drug Abuse Diagnosis (0/1)	0.449	1.58	5.1	0.0245
Violent Fantasies: Escalating Seriousness (0/1)	0.648	1.9	3.9	0.0477
BPRS Total Score	−0.033	0.98	3.9	0.0481
Constant	−2.814	—	—	—

Likelihood ratio χ^2 (191.3, df = 18, $p < 0.0000$).
Pseudo-R^2 (0.298).
[a]Dependent measure: Violence during first 20 weeks following hospital discharge. Variable selection method: forward stepwise.

1 appear to contradict findings from prior research (Barratt, 1994; Link & Stueve, 1994). Specifically, Threat/Control-Override symptoms and the Non-Planning subscale of the Barratt Impulsiveness Scale were found to be negatively associated with subsequent violence. Both of these risk factors represent measures whose appearance in the literature on violence risk assessment is relatively recent. These findings suggest the need for additional research to further refine the role of these measures. To assess the overall accuracy of this risk assessment equation, predicted probabilities were computed for each of the 939 cases, ranging from 0.002 to 0.93, with half the cases lying between 0.05 and 0.26. These probabilities were then submitted to an ROC analysis producing an AUC of 0.81 ($p < 0.001$; see Fig. 1).

Next, a classification tree model was produced (see Fig. 2A). As shown, the classification tree model contained 12 contingent risk factors that sorted the sample into 13 risk groups ranging in predicted probabilities from 0.0 to 0.59 (see Appendix B for a description of those risk factors not also appearing in Appendix A).[10] The

[10]An example of how this classification tree model would be used to assess violence risk may be useful. First, the clinician would assess psychopathy. If a patient scored high on psychopathy, the clinician would next assess the seriousness of prior child abuse for the patient. If a person scored high on this risk factor, the presence of an alcohol or drug abuse diagnosis then would be assessed. If such a diagnosis were applicable, the patient would further be assessed for suicidality. Depending on the outcome of this assessment, the patient would be assessed as having either a 0.59 or 0.38 probability of committing a violent act within the next 20 weeks.

ROC analysis based on the predicted probabilities produced by this model yielded an AUC 0.79 ($p < 0.001$; see Fig. 1). Thus, although these models arrive at assessment of violence risk using markedly different decision processes, they exhibit virtually identical levels of predictive accuracy (Gardner et al., 1996).

We examined the effects of applying two decision thresholds to each of the previously mentioned models (see Table 2). For this illustration, we chose cutoff scores with reference to the base rate of violence in the sample we studied. The prevalence rate of violence during the first 20 weeks after hospital discharge for the full sample was 18.7% (i.e., 18.7% of the patients committed at least one violent act during the first 20 weeks following hospital discharge). We defined any case assigned a predicted probability of violence that was greater than *twice* the base prevalence rate (>37%) as in the "high-risk" category, and any case whose predicted probability of violence was less than *half* the base prevalence rate (<9%) as in the "low-risk" category.

Panels A and B of Table 2 present the distribution of cases obtained by categorizing the predicted probabilities produced by the main effects and standard classification tree models, respectively, using the threshold criteria of twice and half the sample baserate to identify high- and low-risk cases. As shown, 42.9% of the cases (403 out of 939) remained unclassified as high or low risk using the main-effects approach, compared to 49.2% for the standard classification tree model. In other words, using either of these actuarial methods resulted in the classification

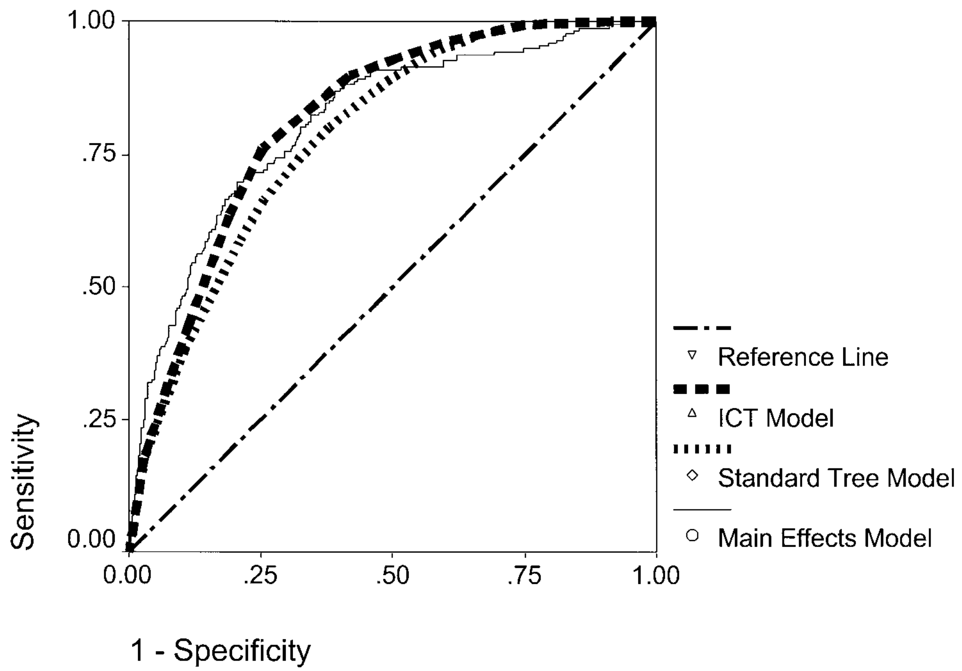
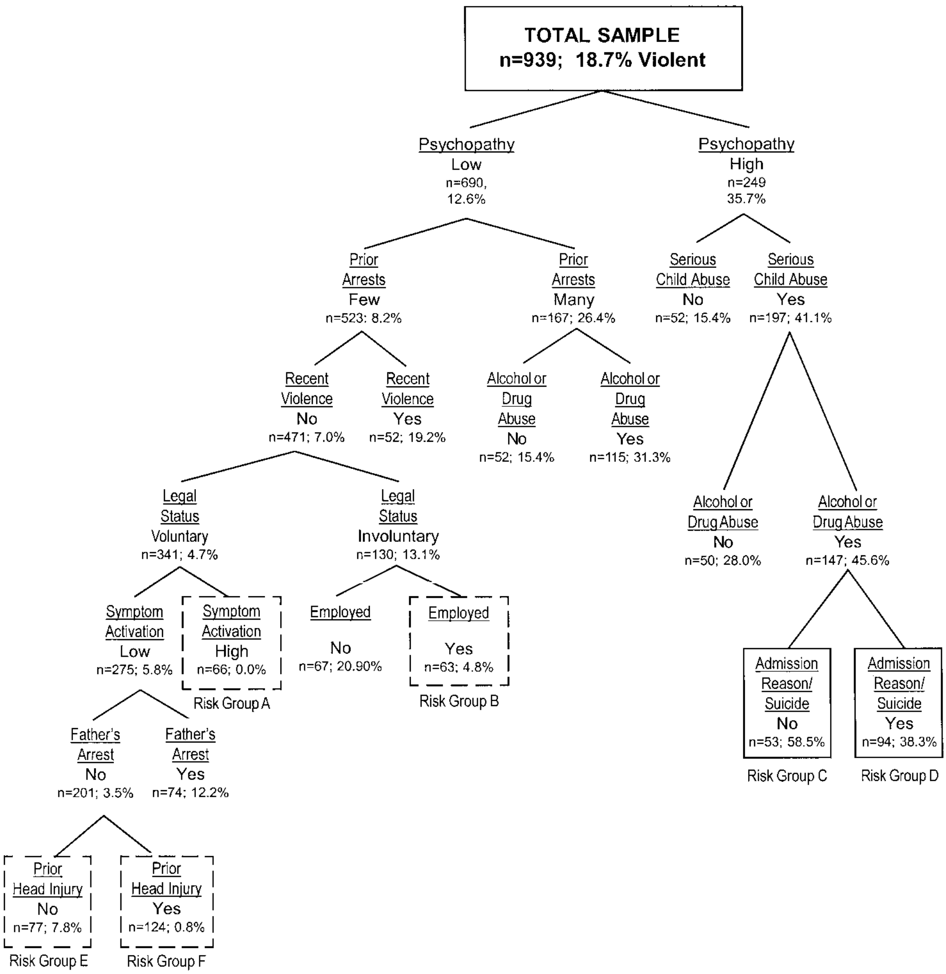


Fig. 1. A comparison of ROC curves: main-effects, standard classification tree, and iterative classification tree models.



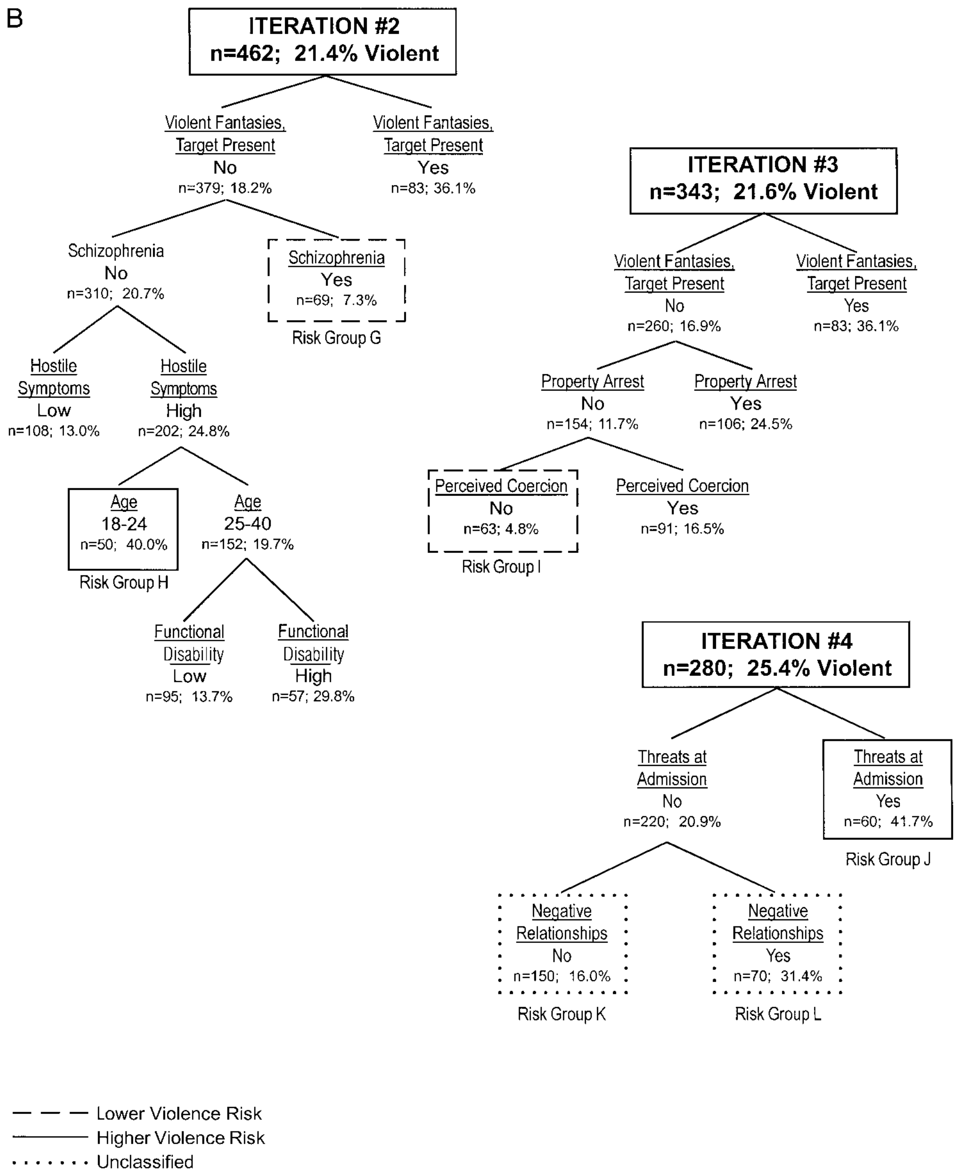
A

Fig. 2. Standard classification tree (A) and iterative classification tree (A and B) models. © 1999.

of between 50% and 60% of the cases as above the 0.37 threshold for identifying high-risk cases or below the 0.09 threshold for identifying low-risk cases.[11]

Finally, we extended the ideas of a tree-based approach with a two-threshold framework to produce a tree-based actuarial violence risk assessment tool that

[11]In terms consistent with those given by the AUC of an ROC analysis, the figures provided in Table 2 can be used to compute the joint probability that a randomly selected violent case will score above 0.37 and a randomly selected nonviolent case will score below 0.09. Specifically, for the standard main effects model (panel A), the probability that a randomly selected violent case will score above 0.37 is given by the ratio $83/176 = 0.47$ (which is the sensitivity for that cutoff) and the probability that a randomly selected nonviolent cases will score below 0.09 is given by the ratio $364/763 = 0.48$ (which is the specificity for that cutoff). Multiplying these probabilities together gives the joint probability ($0.47 \times 0.48 = 0.22$) that both events will occur. Thus, using the main-effects model, there is a 22% chance that a randomly selected violent case will score above 0.37 *and* that a randomly selected nonviolent case will score below 0.09. The corresponding value for the standard classification tree model is 0.16.



B

Fig. 2. (*Continued*).

yields a higher joint probability of classifying cases into high- and low-risk groups. Specifically, we reanalyze those cases designated as "unclassified" using the standard classification tree method. That is, all subjects not classified into groups designated as either high or low risk in the standard classification tree model were pooled together and reanalyzed using the CHAID algorithm as described previously. The

Table 2. Use of Two Thresholds to Classify High- and Low-Risk Cases

Panel A Observed	Main effects model			
	Low <9%	Unclassified	High <37%	Total
Not violent	364	325	74	763
Violent	15	78	83	176
Total	379	403	157	939
Panel B Observed	**Standard classification tree model**			
	Low <9%	Unclassified	High >37%	Total
Not violent	320	363	80	763
Violent	10	99	67	176
Total	330	462	147	939
Panel C Observed	**Iterative classification tree model**			
	Low <9%	Unclassified	High >37%	Total
Not violent	444	174	145	763
Violent	18	46	112	176
Total	462	220	257	939

process of pooling and reanalyzing cases was continued until no additional groups of subjects could be classified as either high or low risk. We refer to the resulting classification tree model as an iterative classification tree (ICT).

The ICT model (see Fig. 2A, B) proceeded through four iterations (or reanalyses). After the first iteration—the point at which standard tree model was terminated—the model classified 477 of the 939 subjects (50.8%) into either the high- or low-risk categories. After the second iteration, the ICT model classified as high or low risk an additional 119 of the 462 subjects (25.8%) who were designated as unclassified at the end of iteration 1. After the third iteration, the model classified as low risk an additional 63 of the 343 subjects (18.4%) who were designated as unclassified at the end of iteration 2. After the fourth iteration, the model classified as high or low risk an additional 60 of the 280 subjects (21.4%) who were designated as unclassified at the end of iteration 3.

Iterating the original recursive partitioning solution, therefore, increased the number of subjects classified as high or low risk from 477 (50.8% of the sample) to 719 (76.6% of the sample; Table 2). At the end of iteration 4, no further groups could be classified as high or low risk; 220 subjects (23.4% of the total sample) remained unclassified by the model. The final ICT model contained a total of 20 contingent risk factors (two of which appear twice)—see Appendix C for a descrip-

Table 3. Summary of Three Models

Model	Area under ROC curve	Percentage classified as high or low risk using two decision thresholds
Main effects	0.81	57.1
Standard classification tree	0.79	50.8
Iterative classification tree	0.82	76.6

Table 4. Bootstrapped 95% Confidence Intervals for the ICT Risk Groups

Risk group	Violent in risk group (%)	95% Confidence interval	
		Lower	Higher
C	58.5	44.7	72.3
J	41.7	28.6	54.8
H	40.0	26.1	53.9
D	38.3	28.8	47.8
L	31.4	20.5	42.3
K	16.0	10.2	21.8
E	7.8	1.9	13.7
G	7.2	1.2	13.4
B	4.8	0.0	10.1
I	4.8	0.0	10.0
F	0.8	0.0	2.4
A	0.0	0.0	4.5

tion of those risk factors in the ICT not also appearing in appendices A or B—that formed 12 risk groups (6 low-risk groups, accounting for 49.2% of the total sample, 4 high-risk groups, accounting for 27.4% of the total sample, and 2 unclassified-risk groups, accounting for 23.4% of the total sample). Reanalyzing the unclassified cases thus resulted in identification of additional groups of cases whose probability estimates for violence were above or below the thresholds of 0.37 and 0.09 set for identifying high- and low-risk cases, respectively.[12]

Evaluating the probability estimates for violence produced by the ICT model yielded an AUC of 0.82 ($p < 0.001$) comparable to AUCs obtained for the standard main effects and standard classification tree models (see Fig. 1). However, the ICT model was able to classify 76.5% of the cases (719 of 939) as high or low risk. This compared with 57.1% and 50.8% for the main-effects and standard-classification tree models, respectively (see Table 3). Furthermore, the joint probability of classifying cases as high or low risk (see footnote 9) was 0.37 for the ICT model, compared to 0.22 and 0.16 for the main-effects and standard-classification tree models, respectively (for a comprehensive review of this issue, see Silver & Banks, 1998).

We did not cross-validate the ICT model. Cross-validation requires that available data be divided into a "learning" sample (or model construction sample) and a "test" sample (or validation sample). However, dividing the sample leaves fewer cases for the purpose of model construction and thus "wastes information that ought to be used estimating the model" (Gardner et al., 1996; p. 43). Thus, to estimate the extent of "shrinkage" likely to occur when the ICT model is used on a sample other than the one on which the model was constructed, we used *bootstrapping* (Efron, 1979; Mooney & Duval, 1993). In conducting this analysis, 1000 random samples with replacement were drawn from the original sample of 939. Table 4

[12]The model described here is intended to illustrate how the ICT method may be used to produce an actuarial risk classification model. This model is, however, not intended for immediate clinical use, as further refinements to the particular risk factors in the model are currently being explored. A full description of the risk factors in the ICT is available from the authors.

presents the 95% bootstrapped confidence intervals for each of the 12 risk groups in the ICT model, in order of decreasing risk. The ranges of these intervals indicate how the ICT is likely to perform on other similar samples.

DISCUSSION

The central conviction that has animated this analysis is that a practical violence risk assessment tool must reflect real-life clinical thinking about the complexity of the nature of violence by persons with serious mental disorders. We believe the classification tree approach does this better than other actuarial methods. Clinicians tend to think about the persons they are evaluating for violence as having certain dominant characteristics that, depending on what those characteristics are, lead clinicians to explore additional characteristics believed to be associated with increased likelihood of violence (Gigerenzer, Todd, & the ABC Research Group, 1999). This is precisely how a tree-based model approaches assessment.

The iterative classification tree model, as presented in Fig. 2A,B, may look quite impenetrable and not at all "practical." However, in clinical use that figure would consist simply of a series of questions that would flow one to the next—through the various iterations as necessary—depending on the answer to each prior question, as is the case in many common diagnostic tools such as DTREE (First, Williams, & Spitzer, 1988) and the Computer-Assisted SCID (First, Spitzer, Gibbon, & Williams, 1991). With current software technologies, the use and scoring of the ICT would be simple, even if the figure demonstrating the model is not.

It is important to note that the particular items in the ICT presented here are not necessarily those that would be most practical in a final violence risk assessment tool. To test the utility of our approach, we used all 134 risk factors in our dataset. In fact, many of these risk factors, such as the first one in the tree, Psychopathy, as measured by the Hare PCL:SV, are rarely available in most treatment or evaluation settings (Elbogen et al., 1998). Therefore, we have developed a version of the tool that incorporates only factors already routinely collected or easily obtainable at low cost during an evaluation (Monahan et al., in press). Only then, and with software, would a practical violence risk assessment tool actually exist.

We use the word "tool" throughout this paper because we see the ultimate goal of this line of research to be the development of a mechanism to provide actuarial information that can usefully influence clinical decisions, rather than the development of a general explanatory model of violence among discharged patients (Quinsey et al., 1998). Thus, classification of a patient as belonging to a high- or low-risk group would be expected to have a substantial impact on decisions about clinical management. For members of the residual group (23.4% of our sample), however, whom the ICT suggests represent an "average" risk of violence, treatment planning may well be based largely on other factors.

Finally, it is important to note that the results reported here reflect relatively short-term predictions of community violence among patients discharged from acute hospital stays. As such, statements of relative risk are in comparison to other discharged psychiatric patients, and not in comparison to a general community sample. The extent to which these results will generalize to other (i.e., community-based) treatment settings, other (i.e., forensic) patient populations, or longer periods of observation (i.e., extending beyond 20 weeks) is not known and must await further research.

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Appendix A

Risk Factors in the Main Effects Model

Risk Factor	Description	Pearson *r* with Violence
Impulsiveness: Non-Planning Subscale	Barratt Impulsiveness Scale (BIS-II; Barratt, 1994)	.05
BPRS Activation Rating	Brief Psychiatric Rating Scale (BPRS; Overall & Gorham, 1962)	−.08*
BPRS Hostility Rating		.08*
BPRS Total Score		−.04
Child Abuse Seriousness	Twelve self-report questions on the type of abuse of a patient experienced as a child by his or her parents (0 = none; 1 = bare hand only, with no physical injury; 2 = with an object, with no physical injury; 3 = resulting in physical injury)	.14***
Employed	Self-report question regarding the patient's paid full- or part-time employment status in the 2 months prior to hospital admission (0 = not employed; 1 = employed)	−.05
Father's Drug Use	Self-report question on whether the patient's father had ever used drugs ex-	.16***

	cessively (1 = weekly/daily; 0 = less often)	
Frequency of Prior Arrests	Patient's self-report of the number of arrests since age 15 (0 = none; 1 = one; 2 = two; 3 = three or more)	.24***
Grandiose Delusions	Rating of the presence of grandiose delusions by trained clinical interviewers	−.01
Involuntary Admission Status	Legal status for the baseline hospitalization, as recorded in hospital admission records (0 = voluntary; 1 = involuntary)	.11**
Mental Health Professionals in Social Network	Proportion of social network members who were also mental health professionals (Estroff & Zimmer, 1994)	−.10**
Anger Scale: Behavioral Rating	Novaco Anger Scale (Novaco, 1994)	.16***
Prior Loss of Consciousness	Self-report of any loss of consciousness due to head injury on the Silver-Caton Head Injury Questionnaire (Silver-Caton, 1989)	.10**
Psychopathy	Hare Psychopathy Checklist: Screening Version (Hart, Hare, & Forth, 1994), a 12-item instrument with each item rated by a trained interviewer on a 3-point scale (low = 0–12; high = 13–24). Following Hart, Cox, and Hare (1995), subjects scoring 13 or higher on the 12 items of the Hare PCL-SV were categorized as probable or definite psychopaths; all other subjects were categorized as nonpsychopaths.	.26***
Drug Abuse Diagnosis	Trained research clinicians using the *DSM-IIIR* Checklist (1 = drug abuse diagnosis; 0 = no such diagnosis)	.17***
Threat/Control-Override Symptoms	Clinically validated affirmative answer to the following questions: (1) Have you believed people were spying on you? (2) Has there been a time when you believed people were following you? (3) Have your believed that you were being secretly tested or experimented on? (4) Have you believed that someone was plotting against you or trying to hurt you or poison you? (5) Did you feel that you were under the control of some person, power, or force,	−.10**

	so that your actions and thoughts were not you own? (6) Have you felt that strange thoughts or thoughts that were not your own were being put directly into your mind? (7) Have you felt that someone or something could take or steal your thoughts out of your mind? (8) Have you felt strange forces working on you, as if you were being hypnotized or magic was being performed on you, or you were being hit by X-rays or laser beams?	
Violent Fantasies: Escalating Seriousness	Self-report to the following questions: (1) Do you ever have daydreams or thoughts about physically hurting or injuring some other persons? and (2) Since the time you first started having these thoughts, have the injuries that you think about gotten more serious, less serious, or have they, always been about the same? (1 = more serious; 0 = less serious or same)	.13***
Violent Fantasies: Single Target Focus	Self-reported answers to the following questions: (1) Do you ever have daydreams or thoughts about physically hurting or injuring some other persons? and (2) Are they usually about the same person, or might they be about many different people? (1 = same person; 0 = different)	.10**

Pearson Correlation:
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Appendix B

Risk Factors in the Standard Classification Tree That Are Not Also in the Main-Effects Model

Risk Factor	Description	Pearson r with Violence
Recent Violence	Self-report of violence in the 2 months prior to hospital admission	.14***

Alcohol or Drug Abuse	Presence of an alcohol or drug abuse diagnosis as measured by research clinicians using the *DSM-IIIR* Checklist	.18***
Admission Reason: Suicide	Chart reviewing hospital admission records	−.01
Father Arrested	Self-report question on whether the patient's father had ever been arrested or convicted of a crime (no = never; yes = at least once)	.15***
Prior Head Injury	Self-report of any head injury (with or without loss of consciousness) on the Silver-Caton Head Injury Questionnaire (Silver-Caton, 1989)	.06

Pearson Correlation:
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Appendix C

Risk Factors in the Iterative Classification Tree That Are Not Also in the Standard Classification Tree or in the Main-Effects Model

Risk Factor	Description	Pearson r with Violence
Violent Fantasies, Target Present	Self-report answers to the following questions: (1) Do you ever have daydreams or thoughts about physically hurting or injuring some other persons? (2) In the last 2 months, have you ever had these thoughts while actually being with or watching the person that you imagine hurting?	.12***
Schizophrenia	Diagnosis of a schizophrenia made by research clinicians using the *DSM-IIIR* Checklist	−.12***
Age	Age at target admission	−.07*
Functional Disability	Sum of self-reported ratings of the level of difficulty for the following activities: (1) housework by yourself; (2) shopping for food or buying things you usually need for yourself; (3) managing your money by yourself (such as keeping track of expenses, paying bills, or making money last until the end of the month); (4) using transportation; (5) making your own meals or cooking	−.01

	for yourself on a regular basis; (6) doing laundry by yourself. Response categories included 0 = none; 1 = some; 2 = a lot; 3 = unable to do it.	
Property Arrest	Arrests for property crimes since the age of 18 as measured by official police records	.11***
Perceived Coercion	MacArthur Perceived Coercion Scale (Gardner et al., 1993)	.03
Threats at Admission	Presence of argumentativeness and threatening verbal statements at the time of admission to the hospital and was measured using hospital admission records.	.06
Negative Relationships	Average number of unique individuals named as involved in a negative relationship with the subject (Estroff & Zimmer, 1994).	.06

Pearson Correlation:
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

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