Arizona Department of Juvenile Corrections
Risk Assessment
Project Findings
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Executive Summary

The primary purpose of this project was to construct an interim risk tool for the Arizona Department of Juvenile Corrections (ADJC). The function of the interim risk tool is to statistically estimate the likelihood that an offender will continue to be involved in delinquent activity, and classify the offender according to their relative risk of continued involvement (Gottfredson, 1987; Krysik & LeCroy, 2002). The goal of statistical risk assessment is to effectively group offenders by risk level in order to allocate resources for higher-risk youth while maintaining validity and consistency in the assessment and decision-making process.

The development of an interim risk tool was constructed through an integrated three step approach: (1) a review of the literature related to modeling risk in juvenile correctional populations was conducted; (2) the interim risk tool was developed and subsequently validated on a separate, independent sample; and (3) risk tool administrators and users were surveyed to determine their perceptions and use of the current ADJC risk prediction instrument.

Historically, the type of information included in risk instruments includes the offender's criminal history, social history (e.g., substance abuse, education/employment, family background, psychological profile), and demographics (i.e., age, gender, race/ethnicity) (Cottle et al., 2001; Krysik & LeCroy, 2002). In most risk tools, the likelihood of recidivism is most closely related to a few consistent variables – criminal history, substance abuse, family background, and school performance.

Method

Data were extracted from the Arizona Department of Juvenile Corrections Youthbase. Records from 1,567 youth released in years 2003 and 2004 were used, allowing for one year of follow-up data.

Construction and validation of the interim risk tool followed five steps recommended in the literature for the successful development and implementation of risk assessment tools (Gottfredson & Snyder, 2005; Krysik & LeCroy, 2002):

1. The outcome measure, recidivism, was defined as return to custody within 12 months.
2. A set of potentially predictive items was specified to include available items in ADJC's Youthbase. These factors included youth demographics (gender, race/ethnicity), criminal history information (data on prior referrals/adjudications), and social history factors (i.e., school performance, substance use, family factors, history of abuse, peer relationships, health and hygiene).
3. The total sample was divided into two random and uniform samples – a construction sample (N = 980) used to construct the interim risk tool and a validation sample (N = 587) used to test the validity and efficacy of the interim risk tool. Tests of bivariate relationships were then conducted between recidivism and the individual predictor variables in the construction sample. A set of predictors found to be significantly related with recidivism were then entered into logistic regression, and using backward elimination a parsimonious set of variables that explained the greatest amount of variance in recidivism was identified. The likelihood in percentage terms that a juvenile will return to custody were then calculated to produce classifications of low-, medium-, and high-risk groups based on the probability of recidivism.
4. The interim risk tool was then tested on the independent validation sample to analyze the tool's ability to accurately distinguish offenders with a high risk of recidivating from those with a low risk.
5. Implementation of the current ADJC risk tool was analyzed to assess contextual issues that affect implementation such as its use and acceptance by key actors in the assessment process (e.g., Psychologists, Psych associates, Youth Program Officer (YPO) III - Caseworker) and the efficacy of risk instruments in making important treatment decisions.

Findings

The interim risk tool includes four factors that were significant in the prediction of recidivism:

1. Age at release
2. Number of prior referrals
3. A history of substantiated physical and/or emotional abuse or neglect
4. Diagnosed as having exceptional educational needs (e.g., learning disability, special education needs).

All but one of these variables have a positive influence on the likelihood of recidivism. That is, the likelihood of recidivism increases with a history of substantiated physical/emotional abuse, increases with exceptional educational needs, and increases as number of prior referrals increase, but decreases as age at release increases.

The interim risk tool allows for the calculation of the likelihood (in percentage terms) that a juvenile will recidivate. For instance, the likelihood of a youth recidivating who is 15.41 years of age at time of release, has 28 prior referrals, is reported to have exceptional educational needs (e.g., learning disability, special education), but does not have a history of substantiated physical/emotional abuse is 88.74 percent. The probability of recidivism for a youth who is 17.35 years of age at release, has eight prior referrals, has no known exceptional educational needs (e.g., learning disability, special education), and does not have a history of substantiated physical or emotional abuse or neglect is 13.23 percent.

Upon calculating the likelihood of recidivism, the distribution of scores were examined in order to classify youth as low-, medium-, or high-risk. Cutoff points for classifying youth by risk level were identified by selecting scores that resulted in the greatest discrimination between low-, medium-, and high-risk groups and subsequent recidivism, and by considering two types of prediction error: false negatives (misclassifying a youth as low-risk when the youth actually recidivates) and false positives (misclassifying a youth as high-risk when the youth does not subsequently recidivate). Considering false

negatives as more serious than false positives, and allowing for the greatest discrimination between low-, medium-, and high-risk groups, the following cutoff points were selected:

1. Low-risk – probability of recidivism is 0.00 to 58.99 percent
2. Medium-risk – probability of recidivism is 59.00 to 78.99 percent
3. High-risk – probability of recidivism is 79.00 percent or higher

Accordingly, twenty-two percent of youth in the validation sample who were classified as low-risk (N = 498) recidivated, forty-eight percent of youth classified as medium-risk recidivated (N = 65), and seventy-one percent of the high-risk group (N = 24) recidivated. Consequently, the recidivism rate for the high-risk group is over three times the rate for the low-risk group, and all three risk levels have recidivism rates that are distinctly different from each other.

Analysis of the interim risk tool was concluded by examining how well the risk instrument differentiates youth by level of risk when considering gender and racial/ethnic subgroups of juveniles. The interim risk tool was able to discriminate between low-, medium-, and high-risk group for males and females, as well as subgroups by race/ethnicity. For instance, low-risk white youth have a 21 percent recidivism rate while low-risk Hispanic youth have a 22.6 percent recidivism rate; high-risk white youth have a 75 percent recidivism rate and high-risk Hispanic have an 80 percent rate. In this case, both Hispanic and white high-risk groups have recidivism rates over three times the rate of the low-risk groups.

Recommendations

It is recommended that ADJC adopt the developed interim risk tool as risk can be predicted with greater precision than is provided by the current ADJC risk prediction instrument. The use of the interim risk tool requires programming into the current ADJC information system and training of risk administrators and users. Training should include information on the scoring of the instrument but also on its predictive validity and the theoretical constructs which support its use. Furthermore, reliability of the risk tool must

be included in the implementation process. Finally, it is recommended that ADJC plan for and carry out subsequent validations of risk tools on a regular basis (e.g., annually) as validity of instruments can change over time.

Introduction

Classifications are used throughout the juvenile justice system (e.g., arrest, disposition, determining level of supervision and intervention, parole). Often, these assessments are "clinical" and based on subjective judgments; yet, systematically and reliably derived statistical assessments are deemed more accurate than clinically trained decision makers. Actuarial/statistical risk instruments generally classify youth as low-, medium-, or high-risk for recidivism by estimating an offender's likelihood of reoffending based on their similarity to others who have recidivated in the past. Accordingly, the goal of statistical risk instruments is to identify a group of offenders with different rates of recidivism and focus intensive treatment interventions on those offenders with the greatest risk of returning to custody.

Research has classified risk assessment into three "generations" (Bonta, 1996). First-generation assessments consisted mainly of "clinical" subjective assessments or relied strictly on professional judgments. The weakness with this approach is that the rule for collecting information and formulating one's interpretation is subject to considerable personal discretion and are often difficult to replicate (Bonta, 1996). Second-generation assessments evolved to identify factors that are embedded in empirically developed instruments. These assessments are criticized for their lack of contribution to rehabilitative/treatment efforts due to their reliance on "static" factors that are historical in nature and insensitive to change over time (such as history of abuse and prior criminal record). Third-generation assessments are also empirically based but include both static and dynamic risk factors (dynamic factors include circumstances or conditions that can potentially be changed, i.e., substance abuse, peer associations, and school performance). Such factors are related to subsequent offending but may also be more effective targets for identifying level of treatment interventions. Research on the current use of risk assessments recommends that both static and dynamic factors be included in classification models in order to develop tools that would allow for both "a *priori* classification of risk" and the targeting of offenders for whom interventions are most likely to reduce subsequent offending (Andrews, Bonta, & Wormith, 2006; Bonta, 1996, 2002).

Risk assessment serves a multitude of purposes including allocating resources in an informed and rational manner; making decisions about level of supervision, intervention, or security level in an efficient manner; and making decisions uniformly. Andrews, Bonta, and Hoge (1990) suggest that the administration of these decisions be based on three principles – risk, need, and responsivity. First, clinical decisions about level of supervision and intensity of services should be guided by the level of criminogenic risk offenders exhibit. For instance, Andrews and colleagues (1986: 377) suggest that "higher levels of supervision may reduce the recidivism of higher risk offenders but will have no such effect on the recidivism of low risk cases;" in fact, the risk principle suggests that the assignment of low-risk offenders to intensive services is a waste of scarce resources and may even increase recidivism. Second, the needs principle identifies targets of intervention (e.g., criminogenic needs), suggesting that recidivism will be reduced when criminogenic needs are met (Andrews et al., 2006; Brown, 1996). For instance, if substance abuse and negative peer relationships are found to be major risk and needs factors then programming should focus on those specific needs to reduce subsequent risk of recidivism. Finally, the responsivity principle suggests that decisions about treatment interventions should consider factors likely to affect an offender's responsiveness to treatment. That is, offenders should be placed in programs that match their personality, motivation, ability, and demographics (e.g., cognitive style, anxiety level, cultural/ethnic group considerations, age, and gender). Together, these three principles have important implications for the efficient use and allocation of agency resources (Andrews et al., 1986; Brown, 1996).

Prediction methods are used to estimate the probable future occurrence of some event or behavior based on how members of similar groups have behaved (Gottfredson & Moriarty, 2006; Krysik & LeCroy, 2002). Many statistical methods have been used in prediction studies including cross-classification tables, multiple regression, logistic regression, discriminant analysis, and a variety of clustering approaches. Several studies have attempted to demonstrate the relative utility of different statistical approaches to criminal justice prediction problems; however, there is no clear-cut empirical advantage of selecting one method over another

(Gottfredson & Moriarty, 2006). Factors that do affect the accuracy of predictions, regardless of the method used, include base rate and selection ratios, sample selection and cross-validation, quality of data including an over reliance on static predictors, and misapplication of risk assessment tools.

The base rate is the relative frequency of an event in the population of interest (i.e., the rate of recidivism in the study population), which is typically expressed as a proportion or percentage (Gottfredson & Moriarty, 2006; Jones, 1996). Van Voorhis and Brown (1996) suggest that low base rates of the behavior to be predicted (e.g., recidivism) are a common prediction problem. Since the base rate of youth who go on to commit future offenses is low, one is never able to predict recidivism with total certainty; indeed, risk prediction is often difficult with events that have very high or very low rates of occurrence. The selection ratio, on the other hand, is the proportion of individuals identified by the prediction method as belonging to the outcome class (i.e., the proportion of offenders who are identified as recidivists by a particular predictive instrument) (Gottfredson & Moriarty, 2006; Jones, 1996). Selection ratios affect the accuracy of predictive instruments because selection ratios may be altered by manipulating scores used to classify individuals as low-, medium-, or high-risk for recidivism (Gottfredson & Moriarty, 2006: 185).

Another common methodological concern in prediction studies is sample selection. Samples used in constructing risk tools must be representative of the population to whom the instrument will be applied and the use of at least two samples is recommended (one for construction and one or more for validation). The rationale for using a separate sample for validation is to test the accuracy of the derived risk model on an independent sample (cross-validation). Cross-validation is important in determining the predictive power of the instrument because the rate of classification using the construction sample will always be inflated (Jones, 1996). The goal of classification methods using cross-validation is to identify a group of offenders with widely different rates of re-offending (i.e., high-risk offenders whose probability of recidivism is three to four times greater than the identified low-risk offender). A classification that assigns all individuals to one category (i.e., low-risk) does not discriminate; one consequence of this is

that predictor items found useful in one location may not prove to be useful in another (Gottfredson & Snyder, 2005). Finally, sample size for prediction studies must be large, consisting of at least 500 cases, assigning half for construction and half for validation.

The quality of data available for a prediction study has significant implications on the accuracy of risk assessment tools. Quality of data can be affected by the extent of missing data and the type of available data. The main effect of missing data is that it reduces the size of the sample when conducting multivariate analysis (Jones, 1996; LeCroy, Krysik, & Palumbo, 1998). Accordingly, variables that have data missing for approximately 10 percent of the sample should be considered unstable/unreliable and excluded from analysis. Data available for prediction studies also can influence the predictive ability of the resulting tool. For instance, researchers suggest that relying too heavily on static predictors (those variables that are unchangeable) undermines the usefulness of risk assessment (Jones, 1996). Yet, some researchers suggest that dynamic risk factors (those that are amenable to change) are limited in criminal/juvenile justice system databases, thus creating an over reliance on static predictors when constructing predictive instruments.

When constructing a risk tool, developers need to be "clear about the intended purpose of any given statistically based risk assessment tool to avoid the problems of application and misapplication so common in the field today" (Gottfredson & Moriarty, 2006:193). For instance, Gottfredson and Moriarty (2006:192) suggest that risk assessments are increasingly "being used to predict success and failure in treatment programs," which is an obvious misapplication of a tool that was constructed to determine public safety risk. Accordingly, the type of assessment being constructed (i.e., risk, need) must remain at the center of the development and implementation processes.

Method

Approach

Development followed five steps recommended in the literature as necessary to the successful development and implementation of any risk assessment instrument (Gottfredson & Snyder, 2005; LeCroy et al, 1998):

1. Clearly defining the behavior to be predicted (the outcome measure)
2. Identifying a set of potentially predictive variables
3. Measuring relations between the predictor variables and outcome measure to construct the risk model
4. Testing the relations/model in an independent validation sample
5. Applying the model in situations for which it was developed (i.e., implementation of the risk tool)

Outcome Measure

The first step in the analysis was to establish the outcome measure. This involves defining the behavior to be predicted, which defines the standard for selecting predictors and testing the validity of results (Gottfredson & Snyder, 2005). The outcome measure for this study was recidivism, defined as "return to custody" within 12 months. This outcome measure was selected because it is commonly used by ADJC. In this study, 29% of youth in the construction sample and 27% of youth in the validation sample recidivated.

Predictor Variables

Potential predictor variables were selected based on their empirical link to recidivism or their theoretical association with delinquency (e.g., Agnew, 1992; Akers, 1985; Cottle et al., 2001; Hirschi, 1969; LeCroy et al., 1998; Shaw & McKay, 1972; Sutherland & Cressey, 1978; Wasserman et al., 2003). Risk factors commonly found to be key predictors of recidivism include history of offending (age at first complaint/adjudication, severity of current offense, number of prior offenses), prior out-of-home placements, emotional stability (learning disability, personality, intellectual ability, mental health

history/needs), school problems, health/hygiene, substance use, abuse as a child, family factors (parental substance use, lack of parental supervision, family structure, family criminality), running away, negative peer relationships, community disorganization, and extreme economic deprivation. Among all of the identified variables, criminal history indicators have commonly been found to be the best predictors of recidivism. Potential predictor variables available for this study included youth demographics (race/ethnicity, gender), criminal history (i.e., age at first referral and first adjudication, number of referrals and adjudications, current offense type), and social history information (i.e., intellectual deficits, substance use, gang affiliation, history of abuse, life skills, family criminality, parental substance use, family financial status, family conflict, education/employment, school problems, and health/hygiene).

Data and Sample

To examine risk factors associated with recidivism, data were collected from the Arizona Department of Juvenile Corrections. The sample was based on the records of 1,567 youth who were released in years 2003 and 2004. The use of these two release cohorts provided an ample interval to obtain recidivism data (one full-year of follow-up). The total sample included 1,354 males (86%) and 213 females (14%), of whom 45% were Hispanic, 34% were Caucasian, 10% were African-American, 5% Mexican National, and 5% Native American. Over 90 percent reported serious alcohol or drug abuse problems ($N = 1,440$). Twenty-nine percent of the youth were diagnosed as having exceptional educational needs (e.g., learning disabilities, special education).

Construction and Validation Samples

Of the number of juveniles available for this study, 60 percent ($N = 980$) were randomly assigned to the construction sample (the sample on which the prediction instrument was developed) and the remaining 40 percent ($N = 587$) were used as a validation sample (the sample reserved for verifying/testing results).

Analysis

Upon identifying the outcome and predictor variables, the next step included testing the relationships between the predictor variables and the outcome measure in the construction sample. Once significant relations were identified in the construction sample, relations were then verified by testing them on a separate, validation sample (cross-validation). The next section describes these results.

Results

Descriptive Statistics

Table 1 compares the construction and validation samples. In both samples, the majority of youth were male, Hispanic, under age 13 at first referral, property offenders, and had serious alcohol/drug abuse problems. Almost half of the sample reported gang affiliation and over two-fifths had 11 or more prior referrals.

Table 1. Comparison of the Construction and Validation Samples

Variable	Construction Sample N (%)	N (%) who Recidivated	Validation Sample N (%)	N (%) who Recidivated
	980	283 (28.9)	587	158 (26.9)
2003 cohort	493 (50.3)	117 (23.7)	334 (56.9)	76 (22.8)
2004 cohort	487 (49.7)	166 (34.1)	253 (43.1)	82 (32.4)
Under age 16 at release	156 (15.9)	96 (61.1)	109 (18.6)	56 (51.4)
Under age 13 at first referral	517 (52.8)	197 (38.1)	286 (48.7)	106 (37.1)
Race/ethnicity				
Hispanic	453 (46.2)	132 (29.1)	259 (44.1)	77 (29.7)
Caucasian	350 (35.7)	103 (29.4)	181 (30.8)	45 (24.9)
African-American	89 (9.1)	27 (30.3)	65 (11.1)	17 (26.2)
Native American	46 (4.7)	12 (26.1)	32 (5.5)	6 (18.8)
Mexican National	40 (4.1)	8 (20.0)	42 (7.2)	12 (28.6)
Other	2 (.2)	1 (50.0)	8 (1.4)	1 (12.5)
Gender				
Male	836 (85.3)	244 (29.2)	518 (88.2)	148 (28.6)
Female	144 (14.7)	39 (27.1)	69 (11.8)	10 (14.5)
Offense Type				
Property	425 (43.4)	123 (28.9)	234 (39.9)	67 (28.6)
Person	201 (20.5)	55 (27.4)	131 (22.3)	39 (29.8)
Drug	170 (17.3)	50 (29.4)	111 (18.9)	19 (17.1)
Public Order	106 (10.8)	31 (29.2)	53 (9.0)	19 (35.8)
Other	76 (7.8)	24 (31.5)	57 (9.7)	14 (24.6)
Missing			1 (.2)	0 (0.0)
11 or more prior referrals	471 (48.1)	171 (36.3)	243 (41.4)	71 (29.2)
Average # of prior referrals	11.2 (5.8)		10.7 (6.2)	

Variable	Construction Sample		Validation Sample	
	N (%)	N (%) who Recidivated	N (%)	N (%) who Recidivated
5 or more adjudications Average # of adjudications	606 (61.8) 5.7 (2.9)	203 (71.7)	335 (57.1) 5.4 (2.9)	108 (68.4)
Youth is diagnosed as having exceptional educational needs, e.g., learning disability, special education	280 (28.6)	103 (36.8)	179 (30.5)	54 (34.2)
Serious alcohol or drug abuse problems with serious disruption of functioning	767 (78.3)	227 (29.6)	531 (90.4)	142 (89.9)
History of substantiated physical or emotional abuse or neglect	114 (11.6)	45 (39.5)	70 (11.9)	24 (15.2)
One or both caregivers and/or siblings are currently incarcerated	149 (15.2)	52 (34.9)	76 (12.9)	30 (19.0)
Gang affiliation	456 (46.5)	148 (32.5)	277 (47.2)	90 (57.0)

To examine how strongly predictor variables of risk are associated with subsequent recidivism, we conducted bivariate tests of statistical significance between recidivism and each predictor variable. Chi-square tests were conducted for each predictor variable with discrete categories. For predictor variables measured at the interval-ratio level of measurement, t-tests were conducted. A significance of .05 was used as the criterion for retention in the study. Table 2 reports the distribution of recidivism for each of the predictor variables and the significance level.

Table 2. Relationship between Risk Variables and Subsequent Recidivism – Construction Sample (*N* = 980)

Variable	Non-Recidivists (*N* = 697) N (%)	Recidivists (*N* = 283) N (%)	Level of statistical significance
Some or serious alcohol/drug abuse problems	641 (92.0)	268 (94.7)	.135
Emotional stability: Excessive responses which prohibit/severely limit adequate functioning	248 (35.6)	117 (41.3)	.091

Variable	Non-Recidivists (*N* = 697) N (%)	Recidivists (*N* = 283) N (%)	Level of statistical significance
Life skills: unable to live independently	106 (15.2)	33 (11.7)	.149
Current family financial stress	221 (31.7)	99 (35.0)	.322
Unemployed or underemployed	409 (58.7)	132 (46.6)	.001
Youth is diagnosed as having exceptional educational needs (learning disability, special education)	177 (25.4)	103 (36.4)	.001
Gang affiliation	308 (44.2)	148 (52.3)	.021
Severe school behavior problems or not attending school/expelled	611 (87.7)	250 (88.3)	.768
Youth has health/hygiene needs	249 (35.7)	90 (31.8)	.242
History of substantiated physical or emotional abuse or neglect	69 (9.9)	45 (15.9)	.008
Substantiated intra-familial sexual abuse	26 (3.7)	13 (4.6)	.531
Conflict in home	429 (61.5)	188 (66.4)	.152
Substance abuse – family	418 (60.0)	192 (67.8)	.021
Conviction/adjudication within the family (caregiver or sibling), currently or within the last ten years	452 (64.8)	208 (73.5)	.009

Note: All percentages reported are valid percentages.

Variable	Non-Recidivists Mean (Std Dev)	Recidivists Mean (Std Dev)	Level of statistical significance
Average age at release	17.3 (.83)	16.4 (.92)	.000
Average age at first referral	13.0 (2.0)	12.1 (1.8)	.000
Average number of prior referrals	10.6 (5.7)	12.7 (5.8)	.000
Average number of adjudications	5.4 (2.7)	6.4 (3.3)	.000

Correlation matrices including the variables that were retained for each group (those with a significance level of .05 or better[1]) were checked to assess the likelihood of multicollinearity. Multicollinearity exists when predictor variables are highly correlated with one another (i.e., correlations higher than .8). None of the correlations exceeded .8; therefore, no variables were excluded from the analysis for reasons of multicollinearity.

Multivariate Analyses for Recidivism

Logistic regression techniques were used to assess risk factors associated with recidivism and to estimate recidivism rates for offenders. Logistic regression is an appropriate statistical procedure when attempting to predict a discrete outcome (i.e., an outcome variable composed of only two categories such as recidivism versus non-recidivism) from a set of predictor variables (Menard, 2001). The main advantage of logistic regression is that few statistical assumptions are required for its use. Furthermore, it generates exact probability values that are constrained between zero and one (Gottfredson & Snyder, 2005; Hosmer & Lemeshow, 1989).

In logistic regression, coefficients (b) tell the change in the log odds of being in the category of interest on the dependent variable (e.g., the change in the log odds of recidivism), associated with a one-unit change in the independent variable, controlling for all other independent variables in the model (Menard, 2001). If the coefficient of a predictor variable is positive, then the probability of recidivism increases as the numerical value of the variable increases, with all other variables being held constant. Conversely, a negative coefficient indicates that larger values of the predictor variable are associated with a diminished probability of recidivism.

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[1] Variables retained included: unemployed/underemployed; youth is diagnosed as having exceptional educational needs; gang affiliation; history of substantiated physical or emotional abuse/neglect; familial substance abuse; conviction/adjudication within the family, currently or within the last ten years; age at release; age at first referral; number of prior referrals; number of adjudications.

Once variables that were significantly related to recidivism were identified through the use of bivariate tests of significance, a system of backward elimination was used to eliminate nonsignificant variables one at a time to identify a parsimonious set of variables. The final model included variables that were significant at the .05 level or better, which, when combined, explained the greatest amount of variance in recidivism. Table 3 presents the results of recidivism, producing a model with four statistically significant variables: age at release, diagnosed as having exceptional educational needs (e.g., learning disability, special education), history of substantiated physical or emotional abuse or neglect, and number of prior referrals. As displayed, all but one of the variables have a positive influence on the odds of recidivism. That is, likelihood of recidivism increases as number of prior referrals increase; likelihood of recidivism also increases with intellectual/educational deficits and with a history of substantiated physical and/or emotional abuse or neglect. Additionally, likelihood of recidivism decreases as age at release increases.

Table 3. Logistic regression results

Variables		b	s.e.	B
Age at release***		-1.0983	.0896	.3334
Intellectual deficits**		.5536	.1727	1.7396
History of substantiated physical abuse*		.5382	.2385	1.7130
Number of prior referrals***		.0633	.0134	1.0653
Constant***		16.6647	1.4932	
-2 Log Likelihood	949.249			
Goodness of Fit	938.557			
Nagelkerke R²	.298			
Model Chi-Square	228.812***			
Degrees of Freedom	4			
Correctly Predicted	75.71%			

***$p<.001$, **$p<.01$, *$p<.05$. $N = 980$.

The percentage of cases correctly predicted by the model (last row of Table 3) shows the overall success of the model in correctly predicting whether an offender was returned to custody. The regression model predicting

recidivism improves our ability to identify offenders most likely to recidivate and not recidivate over chance alone (71.1 percent versus 75.7 percent[2]).

Calculation of Predicted Probabilities

Upon identifying the risk model that explained the greatest amount of variance in recidivism, the next step was to estimate the probability of subsequent recidivism by calculating predicted probabilities. The maximum likelihood coefficients for the four variables shown in Table 3 (listed under the column "b") were entered into the following equation (e is the number 2.718282) (Menard, 2001). The predictions are calculated on the validation sample as opposed to the construction sample from which the equation was derived.

$$Y = \frac{e^{A+B1X1+B2X2+B3X3+B4X4}}{1+e^{A+B1X1+B2X2+B3X3+B4X4}}$$

By calculating predicted probabilities, the interim risk tool reports the likelihood (in percentage terms) that a juvenile will recidivate. For instance, the likelihood of a youth recidivating who is 15.41 years of age at time of release, has 28 prior referrals, is reported to have exceptional educational needs (e.g., learning disability, special education), but does not have a history of substantiated physical and/or emotional abuse or neglect is 88.74 percent. The probability of recidivism for a youth who is 17.35 years of age at release, has eight prior referrals, has no known exceptional educational needs (e.g., learning disability, special education), and does not have a history substantiated physical or emotional abuse or neglect is 13.23 percent.

Upon calculating the likelihood of recidivism, the distribution of scores were examined to determine cutoff points that would allow placement of all juveniles into three risk groups (low, medium, and high). The cutoff points were determined by selecting scores that resulted in the greatest discrimination between low-, medium-, and high-risk groups and subsequent

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[2] 28.9 percent of the construction sample recidivated while 71.1 percent of the sample did not recidivate. Accordingly, our "best guess" would be to predict that an offender did not recidivate, of which we'd be correct 71.1 percent of the time. The regression model improves our ability to correctly predict the outcome to 75.71 percent of the time.

recidivism. Cutoff points were also determined by considering two types of prediction error that occur in prediction models: false negatives and false positives (Jones, 1996). For instance, models may err with a false negative prediction; that is, misclassifying a youth as being likely to succeed (low-risk), when the youth actually recidivates. Second, the model may err with a false positive prediction - misclassifying a youth as being likely to recidivate (a risk), when the youth actually "succeeds." Both types of error are not viewed equally and both have important consequences that should be assessed. False negatives have obvious implications for public safety while the rate of false positives has implications for fairness, equity, and budgeting. Oftentimes, an error that results in identifying an offender as low-risk who then reoffends (false negative) is considered to be the more serious because it can endanger public safety. Accordingly, cutoff scores were based on low levels of false negatives.

Table 4 presents statistics describing the efficacy of the risk tool in estimating recidivism. These statistics include the cutoff points for probability of recidivism, the respective classification/risk level, the number and percentage of cases in each classification group along with their respective recidivism rate.

Table 4. Subsequent Recidivism Rate

Probability of Recidivism	Classification	Cases (%)	Subsequent Recidivism Cases (%)
00 - .5899	Low	498 (84.8%)	110 (22.1%)
.59 - .7899	Medium	65 (11.1%)	31 (47.7%)
.79+	High	24 (4.1%)	17 (70.8%)

N = 587 (validation sample).

In the validation sample, 84.8 percent and 4.1 percent of the assessments were low-risk and high-risk respectively while 11.1 percent were medium-risk. The subsequent recidivism rate of the low-risk group is 22.1 percent compared with 70.8 percent for the high-risk group. That is, the recidivism rate for the high-risk group is over three times the rate for the low-risk group. Accordingly, the three risk levels have recidivism rates that are distinctly different from each other.

Sensitivity Analysis

One final consideration is how well the interim risk tool predicts for different subgroups of the juvenile population – males versus females and subgroups by race/ethnicity. This section presents data demonstrating the discriminating ability of the risk tool for gender and race/ethnicity. All of the sensitivity analyses are based on data from the validation sample, which is independent of the construction sample.

Table 5 presents the relationship between risk level and recidivism for males and females. The interim risk tool classifies approximately 84 percent of females as low-risk, 13 percent as medium-risk, and three percent as high-risk. The subsequent recidivism rates, beginning with females classified as low-risk is 9, 44, and 50 percent respectively. The risk tool classifies approximately 85 percent of males as low-risk, 11 percent as medium-risk, and four percent as high-risk. The subsequent recidivism rate for males so classified is 24, 48, and 73 percent. Accordingly, low-risk males have almost a 24 percent recidivism rate while low-risk females have a nine percent rate; high-risk males have almost a 73 percent recidivism rate and high-risk females have a 50 percent rate.

Table 5. Sensitivity Analysis by Gender

Female			Male		
		Subsequent Recidivism			**Subsequent Recidivism**
Classification	**Cases (%)**	**Cases (%)**	**Classification**	**Cases (%)**	**Cases (%)**
Low	58 (84.1)	5 (8.6)	Low	440 (84.9)	105 (23.9)
Medium	9 (13.0)	4 (44.4)	Medium	56 (10.8)	27 (48.2)
High	2 (2.9)	1 (50.0)	High	22 (4.2)	16 (72.7)

Table 6 reports the ability of the interim risk tool to predict recidivism by different racial/ethnic groups. For example, low-risk white youth have a 21 percent recidivism rate while low-risk Hispanic youth have a 22.6 percent recidivism rate; high-risk white youth have a 75 percent recidivism rate and high-risk Hispanic have an 80 percent rate. For all groups with the exception of American Indians, recidivism increases with increasing risk, and all three of these groups have recidivism rates three times greater than their low-risk counterparts. The interim risk tool does not perform as well for American

Indian youth as for the other racial/ethnic groups; for example, the six American Indian youth who recidivated were classified as low-risk, while the four American Indian youth classified as medium- or high-risk did not recidivate. However, because the number of American Indian youth in the study is quite small, it is difficult to know if the instrument might perform more adequately with a larger sample.

Table 6. Sensitivity Analysis by Race/Ethnicity

Caucasian			Hispanic		
Classification	**Cases (%)**	**Subsequent Recidivism Cases (%)**	**Classification**	**Cases (%)**	**Subsequent Recidivism Cases (%)**
Low	162 (89.5)	34 (21.0)	Low	208 (80.3)	47 (22.6)
Medium	15 (8.3)	8 (53.3)	Medium	36 (13.9)	18 (50.0)
High	4 (2.2)	3 (75.0)	High	15 (5.8)	12 (80.0)

African-American			American Indian		
Classification	**Cases (%)**	**Subsequent Recidivism Cases (%)**	**Classification**	**Cases (%)**	**Subsequent Recidivism Cases (%)**
Low	56 (86.2)	12 (21.4)	Low	28 (87.5)	6 (21.4)
Medium	6 (9.2)	3 (50.0)	Medium	3 (9.4)	0 (0.0)
High	3 (4.6)	2 (66.7)	High	1 (3.1)	0 (0.0)

Note: Analysis by Asian youth and youth identified as "Other" Racial/Ethnic background are excluded from analysis due to their low representation in the sample (N=5 and N=3, respectively).

Conclusion

The purpose of this project was to develop an interim risk tool that predicts recidivism better than the current ADJC risk prediction instrument. In developing the interim risk tool, we performed several statistical procedures which assessed factors related to subsequent recidivism. These procedures included conducting bivariate tests of significance (e.g., chi-square and difference of means t tests), performing logistic regression to assess the contribution of each predictor variable on recidivism, and calculating predicted probabilities to predict the likelihood of subsequent recidivism. The interim risk tool was subsequently tested on an independent validation sample to assess its ability to distinguish offenders with a high-risk of recidivating from those with a low-risk.

The variables that are statistically significant in predicting recidivism include age at release, number of prior referrals, a history of substantiated physical or emotional abuse or neglect, and diagnosed with exceptional educational needs (e.g., special education, learning disability). Results indicate that the interim risk tool can distinguish between low-, medium-, and high-risk groups and subsequent recidivism. Also, the interim risk tool is shown to discriminate among subgroups of the juvenile population (i.e., gender, race/ethnicity).

The variables identified as most predictive of recidivism are generally consistent with those supported in the literature. For instance, educational deficits and a history of abuse/neglect have been shown to be some of the most predictive factors of recidivism; similarly, they have been identified in the literature as targets for effective intervention (Edwards et al., 2005; Fergusson & Horwood, 1995; Hawkins & Lishner, 1987; Wasserman et al., 2003; Widom, 1989). For instance, the American Academy of Child and Adolescent Psychiatry (2001) provides suggestions for addressing the educational needs of incarcerated youth which include developing stronger ties to public school programs, providing comprehensive educational and developmental screenings, and systematically identifying incarcerated youth with special educational needs. Furthermore, a growing body of literature

stresses the importance of addressing underlying trauma associated with a history of abuse or neglect in attempts to reduce delinquent behavior (e.g., U.S. Department of Health and Human Services, 1996; Widom, 1989, 2000). Accordingly, these factors have implications for the rehabilitation of juvenile offenders. A third factor found to be predictive of recidivism – number of prior referrals – is also consistent with research on risk assessment. This literature suggests that the "best predictor of future behavior is past behavior" and that criminal history factors are one of the strongest predictors of recidivism (Gottfredson & Moriarty, 2006: 192).

Recommendations

It is recommended that ADJC adopt the developed interim risk tool as risk can be predicted with greater precision than is provided by the current system (i.e., the interim risk tool provides greater discrimination between high-, medium-, and low-risk cases and used an independent validation sample to test the extent that empirically derived relationships persist across samples). Furthermore, the interim risk tool allows for the calculation of the likelihood (in percentage terms) that a juvenile will return to custody.

The interim risk tool will require programming into the current information system using the predicted probability equation (see page 13) and maximum likelihood coefficients corresponding to the variables that were determined to be most predictive of recidivism (page 12). Once the formula is programmed into a database (SPSS, Excel) along with the corresponding coefficients, risk administrators will be able to enter a youth's score on the four variables to calculate the percentage of risk for return to custody for each juvenile. When implementing such programming, it is necessary to differentiate between missing data and a score of zero that represents the absence of the variable (e.g., a score of zero would indicate that a youth is not diagnosed as having exceptional educational needs). Accordingly, it is important that missing values not be coded with a score of zero. If data are missing from any of the four predictor variables, risk scores can not be estimated.

Reliability of the risk assessment tool must be included in the implementation of the interim risk tool. That is, risk administrators and users need to be trained both in the collection of information on the predictive items but also on the utility of the revised system. Therefore, it is recommended that administrators and users of the risk tool be trained on how the tool is used, its predictive validity, and the theoretical constructs that support its use. This training should also include operational definitions with the items to be scored, as this may also reduce error and increase reliability.

It is also recommended that ADJC plan for the subsequent validation of their risk assessment tool on a regular basis (i.e., annually). Validity of instruments can change over time as juveniles, families, communities, and systems change. The use of a separate independent sample (i.e., cross-validation) should be used for subsequent validation research.

Finally, it is recommended that ADJC examine how best to match treatment according to risk-level and assessed need. Research on risk assessment recommends that programs follow the three principles of risk, need, and responsivity; simply matching programs to an offender's risk level, while ignoring criminogenic needs and responsiveness to treatment, is insufficient for effective programming (Andrews et al., 2006). It is thereby important to match modes of treatment and services with an offender's risk level, intervention needs, and learning style and abilities in order to reduce subsequent recidivism.

References

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology,* 30, 47-87.

Akers, R. (1985). *Deviant behavior: A social learning approach, 3rd ed.* Belmont, CA: Wadsworth.

American Academy of Child and Adolescent Psychiatry (2001). Recommendations for juvenile justice reform. Washington, DC: American Academy of Child and Adolescent Psychiatry. Retrieved online at: http://www.uiowa.edu/~nrcfcp/dmcrc/pdf/everything6.pdf.

Andrews, D.A., Bonta, J., & Hoge, R.D. (1990). Classification for effective rehabilitation: Rediscovering psychology. *Criminal Justice and Behavior,* 17, 19-52.

Andrews, D.A., Bonta, J., & Wormith, J. S. (2006). The recent past and near future of risk and/or need assessment. *Crime and Delinquency,* 52, 7-27.

Andrews, D.A., Kiessling, J., Robinson, D. & Mickus, S. (1986). The risk principle of case classification: An outcome evaluation with young adult probationers. *Canadian Journal of Criminology,* 28, 377-384.

Bonta, J. (1996). Risk-needs assessment and treatment. In A.T. Harland (Ed), *Choosing correctional options that work: Defining the demand and evaluating the supply (*pp. 18-32). Thousand Oaks, CA: Sage.

Bonta, J. (2002). Offender risk assessment: Guidelines for selection and use. *Criminal Justice and Behavior,* 29, 355-379.

Brown, M. (1996). Refining the risk concept: Decision context as a factor mediating the relation between risk and program effectiveness. *Crime and Delinquency,* 42, 435-455.

Cottle, C., Lee, R.J., & Heilbrun, K. (2001). The prediction of criminal recidivism in juveniles: A meta-analysis. *Criminal Justice and Behavior,* 28, 367-394.

Edwards, V.J., Anda, R.F., Dube, S.R., Dong, M., Chapman, D.F., & Felitti, V.J. (2005). The wide-ranging health consequences of adverse childhood experiences. In K. Kendall-Tackett & S. Giacomoni (Eds.), *Victimization of children and youth: Patterns of abuse, response strategies.* Kingston, NJ: Civic Research Institute.

Fergusson, D.M. & Horwood, L.J. (1995). Early disruptive behavior, IQ, and later school achievement and delinquent behavior. *Journal of Abnormal Child Psychology,* 23, 183-199.

Gottfredson, S. D. (1987). Prediction: An overview of selected methodological issues. In D.M. Gottfredson and M. Tonry (Eds), *Prediction and classification: Criminal justice decision making,* (pp. 21-52). Chicago, IL: University of Chicago Press.

Gottfredson, D.M. (1987). Prediction and classification in criminal justice decision making. In D.M. Gottfredson and M. Tonry (Eds)., *Prediction and classification: Criminal justice decision making,* (pp.1-20). Chicago, IL: University of Chicago Press.

Gottfredson, S.D. & Moriarty, L.J. (2006). Statistical risk assessment: Old problems and new applications. *Crime and Delinquency,* 52, 178-200.

Gottfredson, D.M. & Snyder, H.N. (2005). *The mathematics of risk classification: Changing data into valid instruments for juvenile courts.* Washington, DC: National Center for Juvenile Justice.

Hawkins, J.D. & Lishner, D.M. (1987). Schooling and delinquency. In E.H. Johnson (Ed.), *Handbook on crime and delinquency prevention* (pp. 179-221). Westport, CT: Greenwood Press.

Hirschi, T. (1969). *Causes of delinquency.* Berkeley, CA: University of California Press.

Hosmer, D. W. and S. Lemeshow. 1989. *Applied logistic regression.* New York, NY: John Wiley and Sons.

Jones, P. (1996). Risk prediction in criminal justice. In A.T. Harland, (Ed.), *Choosing correctional options that work: Defining the demand and evaluating the supply* (pp. 33-68). Thousand Oaks, CA: Sage.

Krysik, J., & LeCroy, C.W. (2002). The empirical validation of an instrument to predict risk of recidivism among juvenile offenders. *Research on Social Work Practice,* 12, 71-81.

LeCroy, C.W., Krysik, J. & Palumbo, D. (1998). *Empirical validation of the Arizona risk/needs instrument and assessment process.* Tucson, AZ: LeCroy and Milligan Associates, Inc.

Menard, S. (2001). *Applied logistic regression analysis, 2nd ed.* Thousand Oaks, CA: Sage.

Shaw, C. & McKay, H. (1972). *Juvenile delinquency and urban areas.* Chicago, IL: University of Chicago Press.

Sutherland, E., & Cressey, D. (1978). A sociological theory of criminal behavior. *Criminology,* 10, 77-83.

U.S. Department of Health and Human Services. (1996). *Third national incidence study of child abuse and neglect, 1986-1993.* Washington, DC: U.S. Dept. of Health and Human Services, Administration for Children and Families.

Van Voorhis, P. & Brown, K. (1996). Risk classification in the 1990s. National Institute of Corrections.

Wasserman, G.A., Keenan, K., Tremblay, R.E., Coie, J.D., Herrenkohl, T.I., Loeber, R., & Petechuk, D. (2003). Risk and protective factors of child delinquency. Washington, DC: Office of Justice Programs, Office of Juvenile Justice and Delinquency Prevention.

Widom, C.S. (1989). Child abuse, neglect, and violent criminal behavior. *Criminology, 27, 251-271.*

Widom, C.S. (2000). Childhood victimization and the derailment of girls and women in the criminal justice system. In B. Richie, K. Tsenin & C.S. Widom (Eds.), *Research on women and girls in the criminal justice system (*pp. 27-36). Washington, DC: Office of Justice Programs, National Institute of Justice.

Wormith, J.S. & Goldstone, C.S. (1984). The clinical and statistical prediction of recidivism. *Criminal Justice and Behavior,* 11, 3-34.