Enhancing Parole Decision-Making Through the Automation of Risk Assessment

Submitted to:
Georgia Board of Pardons and Paroles

April 29, 2003

Applied Research Services, Inc.
"turning data into decisions"

Project Staff

Applied Research Services, Inc.

Tammy Meredith, Ph.D., Project Director

John Speir, Ph.D.

Sharon Johnson

Heather Hull

Georgia Board of Pardons and Paroles

John Prevost, Director of OCJR

Alan Shope, DBA for OCJR

Nyit Wah Young, Oracle Programmer

Table of Contents

Chapter 1: Risk Assessment

How do we know if a parolee will be arrested while under our supervision? We cannot know for certain. Yet by using the tools of science, we can improve upon our professional judgment by *mathematically* assessing risk. An officer with insight into a parolee's likelihood of re-offending can make more informed case supervision decisions. This idea exemplifies the Georgia Board of Pardons and Paroles' philosophy of "results driven supervision," which encourages the use of research to improve our ability to address the needs of parolees in order to enhance their chances of successful integration into the community.

The development of risk assessment instruments is based on the premise that certain factors (characteristics of an offender or his environment) can be used to predict an offender's risk of future criminality. Correctional professionals have traditionally relied on clinical and professional judgment to predict the behavior of offenders. We can now add to that a sizable body of research, emerging over the past twenty years, that identifies factors statistically predictive of recidivism in order to create and validate actuarial risk instruments.

Actuarial risk instruments have focused primarily on *static*, or unchanging predictors of recidivism, such as age and prior criminality. Today, empirically-derived assessment instruments are evolving to include both static and *dynamic* predictors of recidivism, or those factors that can change over time, such as offender attitudes and behavior while under correctional supervision. This trend is confirmed by the work of Gendreau and colleagues (1996) in identifying the 10 static and 7 dynamic risk factors that consistently surface across 131 recidivism studies published between 1970 and 1994 (most importantly age, prior record, antisocial personality, companions, and criminogenic needs -- which establish standards of conduct and rational for engaging in antisocial behavior).

Composite risk scales are the most powerful predictors of recidivism.

Despite the identification of 17 prime risk factors, Gendreau and his colleages note that *composite risk scales*, which summarize a variety of risk factors, remain the most powerful predictors of recidivism. Today, many correctional agencies are adopting existing and well-tested composite risk scales. Some are developing their own scales, based upon data analyses performed on their own population of offenders. To assess the empirical support for various risk assessment options, we identified 42 risk assessment studies published in the past twenty years (see Table 1). This body of literature guided the Georgia Board of Pardons and Paroles in developing an actuarial risk assessment method for the assignment of supervision level for 20,000 active parolees.

Table 1. A Review of Risk Assessment Studies (N=42)

Study	Sample	Sample Type	Sample Size	Includes Females?	Instrument	Validation?
Ashford & LeCroy, 1988	Parolees	Juveniles	107	Yes	Wisconsin Juvenile Probation Aftercare Risk Instrument	Yes
Austin & Litsky, 1982	Probationers and parolees	Adults	12,526	Yes	Nevada's Initial and Final Risk Assessment Instruments	Yes
Austin, Litsky, McCarthy, 1989	Parolees	Adults	558	Yes	D.C. Department of Corrections Community Risk Instrument	Yes
Bonham, Janesksela, Bardo & Iacovetta, 1984	Parolees	Adults	350	Unknown	Kansas Adult Authority Instrument (12 items)	Yes
Bonta & Motiuk, 1985	Offenders in halfway houses	Adults	164	No	LSI	Yes
Bonta & Motiuk, 1987	Inmates	Adults	384	No	LSI	Yes
Bonta & Motiuk, 1990	Inmates	Adults	580	No	LSI	Yes
Bonta & Motiuk, 1992	Inmates	Adults	580	No	LSI	Yes
Bonta, 1989	Jail Inmates	Adults	126	No	LSI	Yes
Bonta, Pang, & Wallace-Capretta, 1995	Female parolees	Adults	81	Yes	Statistical Information Recidivism Scale (SIR)	Yes
Brennan & Oliver, 2001	National sample of offenders from jails, probation, community corrections, parole & prison	Adults	3,455	Unknown	COMPAS	Yes
Brennan & Oliver, 2002	Probationers	Adults	635	Yes	COMPAS	Yes
Brennan & Wells, 1997	Parolees	Adults	319	Unknown	COMPAS	Yes
Copas & Marshall, 1998	Offenders convicted or released from prison in 1987	Both	14,000	Yes	OGRS (Offender Group Reconviction Scale)	Yes
Cottle, Lee & Heilbrun, 2001	Meta-analysis of offenders between 12 & 21 with at least one prior arrest	Juveniles	N/A	Yes	None — Meta-analysis	N/A
Coulson, Ilacqua, Nutbrown, Giulekas, & Cudjoe, 1996	Female inmates	Adults	526	Yes	Self-Administered LSI	Yes
Dowden & Andrews, 1999	Meta-analyic review of studies of female offenders	Both	N/A	Yes	None — Exploratory Research	No
Dowdy, Lacy & Unnithan, 2002	Males in half-way house	Adults	140	No	LSI	Yes
Funk, 1999	Juveniles assigned probation or referred to DJJ	Juveniles	500	Yes	None — Exploratory Research	N/A
Gendreau, Little & Goggin, 1996	Meta-analysis of 131 studies on recidivism	Adults	N/A	Yes	LSI-R, SFS, Wisconsin, MMPI, PCL	N/A
Gottfredson & Gottfredson, 1985	Federal inmates	Adults	2,382	Yes	None — Exploratory Research	N/A
Hanlon, O'Grady & Bateman, 2000	Parolees	Adults	237	Yes	Addiction Severity Index (ASI)	Yes
Harm & Phillips, 2001	Female recidivists in an Arkansas prison	Adults	38	Yes	None — Exploratory Research	No
Jung & Rawana, 1999	Probationers	Juveniles	250	Yes	Ministry Risk/Need Assessment Form (MRNAF)	Yes
Kirkpatrick, 1999	Female offenders under intensive community supervision	Adults	169	Yes	LSI-R	Yes
Kirkpatrick,1998	Offenders under intensive communtiy supervision	Adults	484	Yes	LSI-R	Yes
Kroner & Mills, 2001	Inmates	Adults	97	No	Psychopathy Checklist-Revised, LSI-R, HCR-20, Violence Risk Appraisal Guide, Lifestyle Criminality Screening Form	Yes
Loucks & Zamble, 1999	Female inmates	Adults	100	Yes	None — Exploratory Research	N/A
Lowenkamp, Holsinger & Latessa, 2001	Inmates	Adults	442	Yes	LSI-R	Yes
Loza & Loza-Fanous, 2001	Federal inmates	Adults	68	No	Self-Appraisal Questionnaire (SAQ), LSI-R, GSIR, PCL-R, VRAG	Yes
Loza & Simourd, 1994	Inmates	Adults	161	No	LSI	Yes
Morgan, 1994	Probationers	Adults	266	Yes	None — Exploratory Research	No
Motiuk, Bonta, & Andrews, 1986	Males in halfway houses	Adults	147	No	MMPI & LSI	Yes
Motiuk, Motiuk & Bonta, 1992	Probationers	Adults	97	No	Self-Report and Interview-Based LSI	Yes
Motiuk, Motiuk & Bonta, 1992	Inmates	Adults	100	No	Self-Report Inventory & LSI	Yes
Olson & Lurigio, 2000	Probationers	Adults	2,438	Yes	Data collection form created by author to capture probationer, offense, & sentence characteristics	No
Quinsey, Harris, Rice & Cormier, 1998	Offenders from the Oak Ridge mental health facility	Adults	685	No	VRAG (Violence Risk Appraisal Guide)	Yes
Sims & Jones, 1997	Probationers	Adults	2,850	Yes	North Carolina Probations Risk Assessment Instrument	Yes
Smith & Aloisi, 1999	2nd time juv. offenders brought to a specific NJ family court	Juveniles	298	Yes	7-item instrument developed by authors	No
Tollett & Benda, 1999	Youth released from the Serious Offender Program in AK	Juveniles	244	Yes	None — Exploratory Research	N/A
Werner & Palmer, 1976	Participants in CACentral Valley Com Tx Project	Juveniles	336	No	Jesness Psychological Inventory — 11 items	Yes
Wheeler & Hissong, 1990	Probationers	Adults	891	Unknown	Georgia Probation Risk-Assessment Instrument	Yes
Wright, Clear & Dickson, 1984	Probationers	Adults	366	Unknown	Wisconsin Risk-Assessment Instrument (probation)	Yes
Zimmerman, Martin, Rogosky, 2001	Inmates	Adults	1,038	Unknown	8-factor instrument developed to predict success in a community corrections center (low risk)	Yes

Problems with Risk Assessment Studies to Date

Many studies suffer from empirical limitations which make it difficult to draw clear conclusions about the effectiveness of selected risk assessment models. One of these limitations is small sample size. As seen on Table 1, the sample size of nearly two-thirds of the studies examined is 500 offenders or less – one in six studies includes 100 or fewer offenders. Only six of the studies examined have sample sizes over 1,000. A small sample size can make it mathematically impossible to assess the relationships between individual risk factors, risk scales, and recidivism.

Studies are based on small samples and exclude females.

Another weakness in the research literature is the development and validation of risk assessment models that exclude female offenders. Only one-half of the studies in Table 1 include females. Even when females are included, there are typically so few cases of recidivating females that a proper assessment of the relationship between risk factors and recidivism is impossible. For example, the Gottfredson & Gottfredson (1985) study of 2,382 released prisoners included only 120 females. The study's overall recidivism rate of 36%, if applied to females, would produce a maximum of only 43 female offenders who recidivated (the recidivism rate for females is generally lower than for males).

To overcome these pitfalls, the current study is based on a recent sample of 6,327 parolees, including 809 females (13%). Only one study published in the research literature to date (Austin & Litsky, 1982) included more offenders. No study to date has included more females.

Summarizing the Literature with Meta-Analysis

It becomes difficult to sort through the literature on risk assessment and draw any sweeping conclusions. Due to differences in study design and purpose, much of the literature on risk assessment is contradictory. While one group of studies may find that certain variables are predictive of criminality, another group may find the same factors not statistically significant. Meta-analytic research is an important tool for investigating the entire body of literature on a topic to identify the factors that are most strongly correlated to the outcome being examined.

Much of the research on risk assessment is contradictory.

Gendreau's (1996) meta-analysis examined 131 studies and 1,141 factors correlated with adult recidivism. The study found many factors were strong predictors of adult recidivism, including: risk scales, prior record, antisocial personality, companions and criminogenic needs. These findings provide guidance about potential factors to be considered for future risk instruments.

A meta-analysis on female offenders was conducted by Andrews and associates (1990) and re-examined with the inclusion of more recent studies by Dowden & Andrews (1999). This analysis of 26 studies identified criminogenic need targets, particularly family processes, as the strongest predictors of treatment success and reduced recidivism among women. The study also found that outcomes were stronger when treatment targeted high risk females as opposed to lower risk females. Finally, a meta-analysis on 23 juvenile recidivism studies conducted between 1993 and 2000 identified the strongest predictors of juvenile recidivism as offense history, age at first commitment, age at first contact with the law, and a history of non-severe pathology (Cottle et al., 1999). Formal risk scales were also found to be a significant predictor of risk behavior among juveniles.

Static vs. Dynamic Risk Factors

While the meta-analyses are critical to the advancement of risk assessment instrument development, they also represent the first body of research to confirm the importance of distinguishing between static and dynamic risk factors. We now have empirical research to support including *both* types of factors when predicting criminal behavior.

The Level of Service Inventory (LSI)

LSI is the most well known risk assessment in corrections.

The Level of Service Inventory (LSI), and now its revised version, the LSI-R, is probably the most well known risk assessment instrument in the corrections world and has been the focus of much research. The LSI-R is composed of 54 items that are designed to assess ten areas of risk/needs (Andrews & Bonta, 1995). A trained professional conducts a semi-structured interview in order to estimate an offender's probability of re-offending within one year. The LSI was initially used by the Ministry of Correctional Services in Ontario to classify probationers and parolees. The instrument is now used in a variety of settings in both the United States and Canada including community corrections (primarily halfway houses) and prisons. The LSI-R can be administered via a computer-scored or hand-scored format. Regardless of how the assessment is administered, it takes approximately 30-45 minutes to complete. Administration costs associated with the LSI-R instrument vary widely based on the administration/interpretation method used, the vendor supporting the instrument, and the volume of assessments used, but the computer-based version of the LSI-R with interpretation will average about $5 per assessment.

Most studies have found the LSI and LSI-R scores are marginal to moderate predictors of recidivism, institutional performance, and community corrections success (Loza, Simourd, 1994; Motiuk, Bonta, Andrews, 1986; Motiuk, Motiuk, Bonta, 1992; Bonta & Motiuk, 1987; Bonta & Motiuk, 1985; Bonta & Motiuk, 1990; Bonta & Motiuk, 1992; Kirkpatrick, 1998; Lowenkamp, Holsinger, Latessa, 2001; Coulson, Ikacqua, Nutbrown, Guilekas, Cudjoe, 1996). However, with the exception of three studies, this research focuses almost exclusively on Canadian correctional populations.

Dowdy, et al (2002) found weak statistical relationships between the LSI/LSI-R score, program success, and recidivism for a sample of offenders sentenced to a halfway house in Colorado. The authors acknowledge that the LSI appears to have utility in Canadian populations, but caution that the predictive validity of the LSI/LSI-R on U.S. offender populations remains questionable. The applicability to U.S. female populations also remains questionable. While Coulson, et al (1996) conclude that the LSI/LSI-R is useful for assessing Canadian female offenders, they note lower risk scores among females in general. The fact that only 20% of the LSI/LSI-R studies listed in Table 1 include women, with only two studies on U.S. populations (Kirkpatrick, 1998; Kirkpatrick, 1999), the application to female offenders becomes speculative at best.

LSI Competition

Compared to the MMPI, which is the standard in psychological assessment, the LSI/LSI-R has been found to produce significantly higher correlations with correctional program failure and re-incarceration (Motiuk, et al, 1986). However, Kroner & Mills (2001) report that when the LSI-R is compared to four other assessment instruments, it is not found to be "statistically" superior.

While the LSI enjoys much notoriety, other less time and cost consuming assessment methods have been proven just as effective. Loza & Loza-Fanous (2001) report that the Self-Appraisal Questionnaire (SAQ), with its 67 true/false questions administered by a paraprofessional to a group of offenders during a 15-20 minute interview, performs as well as the LSI in predicting recidivism (new offenses and parole violations).

Today, other assessment instruments are available. The COMPAS, a statistically based computerized risk assessment instrument developed by Northpointe Institute for Public Management in Michigan, is designed to assess key risk factors to assist in making decisions about the placement of offenders in the community. It assesses four risk areas: violence, recidivism, failure to appear (flight), and community non-compliance (technical violations). The instrument also has the ability to create a criminogenic needs profile which examines criminal history factors, substance abuse needs, vocational/education problems, social environment, and criminal personality. The software is periodically refined in relation to criminological theory and validation research. The authors developed the instrument using a national sample of parolees, prisoners, and probationers (n=3,455) and have conducted several validation studies, including a sample of New Jersey parolees (n=319) and New York probationers (n=635) (Brennan & Oliver, 2001; Brennan & Oliver 2002; Brennan & Wells, 1997). In all cases the developers concluded that the instrument had high psychometric reliability, that the risk and needs scales were consistent with findings in criminological literature, and that the correlations between the scales were consistent with current criminological theory. COMPAS is currently being used in 50 agencies, including all probation offices in New York state. A full assessment (which includes all components of the COMPAS instrument) requires 30-45 minutes to complete, and costs $4 for each administration (however, the cost can be reduced based on the volume of assessments used).

States Develop Their Own Risk Instruments

Many state correctional agencies develop their own risk assessment instruments in order to more accurately identify and weigh risk factors according to the particular nuances of their offender population. Several validation studies have been conducted on risk instruments developed by individual states. Risk instruments in North Carolina, Nevada, Kansas, and Washington DC were found to be useful at predicting offender risk (Sims & Jones, 1997; Austin & Litsky, 1982; Bonham et al., 1984; Austin, Litsky & McCarthy, 1989). However, studies examining the predictive validity of risk instruments on demographic populations outside the state where the instrument was developed have not been promising. For example, Georgia's probation risk assessment instrument was not found to be a valid classification tool on a sample of Harris County, Texas probationers (Wheeler & Hissong, 1990).

Studies have also closely examined the Wisconsin risk assessment instrument which was labeled by the National Institute of Corrections as a "model system." The Wisconsin probation risk-assessment instrument was tested on a sample of probationers from New York City, and the Wisconsin Juvenile Probation and Aftercare Risk instrument was tested on a sample of juvenile youth from Arizona (Wright et al., 1984; Ashford & LeCroy, 1988). In New York, the Wisconsin instrument was found to be a poor gauge of performance on probation, but was found to be fair as a classification tool. When the juvenile instrument was applied to Arizona delinquents, the instrument was unable to discriminate between recidivists and non-recidivists. Findings such as these highlight the need for caution when applying risk instruments across geographic populations.

The Georgia Parole Risk Assessment Project

The Georgia Board of Pardons and Paroles (Parole Board) commissioned Applied Research Services (ARS) to create two innovative risk assessment instruments for the purposes of informing supervision level assignment decisions. Currently, parole officers conduct pencil and paper assessments on all new parolees entering supervision, and re-assessments after the first 90 days and every six months thereafter on all active parolees. On a typical two-year case, an officer would devote at least two hours of work time completing assessments (initial assessment, re-assessment in nine months, and then re-assessment every six months). These assessments are used to guide decisions about supervision level placement (minimum, medium, maximum), which ultimately determines the level of staff resources devoted to a case.

The goal is to replace officer time in completing existing assessments with a computer program that generates risk scores from operational data.

Over a two year period, a research team from the Parole Board, Department of Corrections and ARS worked on the risk assessment concept and implementation. An analysis found that the data collected by parole officers each day through the Board's case management system was sufficient to support the development of new Georgia parole risk assessments. Their goal was to eliminate the officer time required to complete the existing risk instruments by implementing a computer program that would automatically generate risk assessment results using real-time operational data.

The Board's innovative case management system, Field Log of Interaction Data (FLOID), is used daily by parole officers to log all case details and interactions (including any technical violations, new arrests, and convictions while under supervision). This data was complied on a cohort of 6,327 offenders that completed parole supervision within the 7-month time period of July 2000 through January 2001. Two statistical models were developed to predict the risk of recidivism for each parolee, defined as the probability of an arrest for a new offense while under supervision. The first model uses only those static risk predictors known about an offender on the first day of supervision and the second model adds dynamic risk predictors that change with daily supervision interaction (employment, drug test results, program participation). The statistical models are translated into computerized equations that can be solved on any given day for any offender by plugging in the values for the risk factors which come from the daily updated FLOID system.

We have yet to identify anoter state using a similar approach to incorporating real-time data into an automated system to assess parolee risk. Chapter 2 of this report describes the research and methods involved in this study, as well as the two risk assessment instruments developed. It describes the operational testing of the first instrument and reactions from the field staff. Chapter 3 describes the validation studies and establishes that the new risk assessments have *predictive validity* comparable to well established instruments (it works as well, or better, than other methods of predicting who will recidivate). These assessments have distinct advantages over the well-established instruments: they require no staff time, they incur no cost on the agency per assessment, and they are specifically tailored to the Georgia parolee population. Finally, Chapter 4 outlines the next phase of this project.

Chapter 2: The Georgia Automated Parole Risk Assessments

Two Georgia Parole automated risk assessment instruments were developed through extensive analysis of data collected from two sources: the Georgia Department of Corrections Offender Tracking Information System (OTIS) Inmate Research File and the Board of Pardons and Parole's Field Log of Interaction Data (FLOID). Each instrument is computer-generated, as opposed to a pencil and paper assessment. Computer programs executed by the Board's Research Unit access existing OTIS and FLOID data to compute a risk score for each offender on parole. This "estimated risk level" is made available to parole officers through the existing parole case management and reporting system for the purpose of informing the initial supervision level decision and subsequent re-assessments of the need to alter supervision level assignments. The complete process for providing this automated information to officers in the field is in the final testing phase (See Chapter 4).

The Collection and Use of Data

Currently, Georgia parole officers manage caseloads that vary from 40 to 90 parolees per officer. Each officer has a laptop computer and is required to enter all data pertaining to parolee performance and parolee-officer interactions into the FLOID case management system, a Lotus Notes-based relational database. To assist the officer in entering data on new assignments, the FLOID system is fed basic information from the corrections prison data (offender identifiers, offense information, demographics, criminal history captured at prison classification, etc.). FLOID data includes a parolee's residence, place of employment, drug test results, enrollment in programs, technical violations, reprimands, and the number and type of monthly officer contacts recorded regularly for each parolee. The data is reviewed periodically by parole Chiefs for accuracy and completeness. It is used regularly by Chiefs to review and assess proper case supervision.

FLOID data can be easily accessed by an officer at anytime through Parole's *Thelma Lou* report system. That system allows officers and managers to produce a multitude of pre-designed reports utilizing FLOID data. These reports serve primarily to assist with the management of cases, manpower, and to assess the accuracy of data entered into FLOID. Examples of the types of reports that can be run include: lists of all parolees under maximum supervision in a field office, caseloads per officer, face-to-face interactions per parolee, and the number of parolees with technical violations, arrests and revocations.

The Study Cohort

All offenders who completed parole supervision during the seven-month period of July 2000 through January 2001 were included in the current study (n=6,327). The outcome of interest was "arrest for a new offense" during parole supervision, which is measured on the FLOID arrest table (which contains a record of each arrest incident for all parolees). The selection of an outcome variable was made by a working team of ARS, Parole, and Corrections representatives following an extensive analysis of potential outcome measures (technical violation, revocation, warrant, arrest, conviction).

The arrest information is collected and entered into FLOID by parole officers during the course of monitoring cases. The FLOID arrest table is linked by a unique identifier (Inmate Number) to other FLOID tables and the corresponding prison episode record in the Correction files (OTIS). An incident was defined as an arrest only if it included a new offense charge (some accompany a technical violation); an arrest for a technical violation alone did not qualify.

48% of the study cohort was arrested for a new offense while on parole.

Of the cohort of 6,327, a total of 48% were arrested for a new offense while under parole supervision. In addition, 26% were arrested for a technical violation alone and 31% had their parole revoked. The average length of parole was 22 months. Three-fourths of the parolees were originally convicted and sent to prison for a property offense or drug offense (73%). The majority of parolees were male (87%) and African-American (64%).

The cohort was randomly divided into two samples – referred to as the "estimation" and "validation" samples (each with approximately 3,100 parolees). The new risk assessments were developed on the estimation sample and tested on the validation sample (see Chapter 3).

The Initial Risk Assessment

A risk assessment is currently completed when a parolee begins supervision (initial risk assessment). The new automated initial risk assessment was developed to contain only *static* predictors of risk. Static predictors include those factors that are known on the first day of supervision and will not change during the course of parole supervision.

Over 40 potential static predictor variables were identified in the corrections OTIS database, ranging from demographic information (age, race, sex, IQ), social background (family life, employment history, mental health and substance abuse history), offense information, prison behavior, and extensive prior record measures. The OTIS information is collected and entered during the prison diagnostic stage (including self-report and diagnostic assessment), the parole clemency decision stage (following examiner investigations prior to parole release) and computed automatically (some prior record information is accumulated automatically in OTIS upon a prisoner's return).

A multivariate logistic regression analysis was conducted to predict arrest as a function of key offender and offense characteristics. The outcome measure in this study is dichotomous (Yes / No), rendering ordinary least squares (OLS) regression an inappropriate statistical technique. The multivariate ordinary least squares (OLS) regression assumption of normally distributed error terms is violated with a dichotomous dependent variable, producing biased parameter estimates (Hosmer & Lemeshow, 1989). This would lead to the inappropriate selection of risk assessment "factors" or variables. The nonlinear logistic regression technique does not have a similar error term assumption which permits the estimation of unbiased regression coefficients (factor weights).

The risk assessments were developed through multivariate logistic regression analysis.

Statistical model building, or selection of the final factors, was conducted according to the strategies outlined by Hosmer & Lemeshow (1989), testing each predictor variable individually and using the likelihood ratio and Wald tests to aid in variable selection. The final model calculates the probability of the outcome (probability of arrest) for each offender in the cohort, given his / her individual case characteristics. Table 2 below presents the 9 static risk factors included on the initial assessment model.

Table 2. Initial Risk Assessment Logistic Regression Model: The 9 Risk Factors of Arrest for a New Offense

Variables	Variable Description	B	S.E.	Sig.	Odds Ratio
Static Factors:					
AGE_SENT	Age at Sentencing	-.046	.00	.00	0.96
PROPERTY	Most Serious Offense Was Property (yes/no)	.415	.09	.00	1.51
DRUGS_S	Most Serious Offense Was Drug Sales (yes/no)	.483	.12	.00	1.62
P_INCAR	# Prior Juvenile & Adult Incarcerations	.225	.03	.00	1.25
TSALEPO	# Prior Drug Sales/Possess Convictions	.093	.04	.02	1.10
PARPROB	Prior Parole or Probation Revocation (yes/no)	.526	.10	.00	1.69
MHEALTH	History of Mental Health Treatment (yes/no)	.270	.11	.01	1.31
ASSAULT	History of Assault Offenses/Behavior (yes/no)	.232	.10	.00	1.38
DRUGAL	History of Drug or Alcohol Abuse (yes/no)	.253	.09	.00	1.29
Constant		.072	.17	.67	1.08

65% of the cases were correctly classified by the model (arrested vs. not arrested)

The Risk Re-Assessment

In addition to the 40 potential static predictor variables identified in the corrections data, over 35 potential *dynamic* predictor variables were identified in the parole case management data. The dynamic factors change over time, and include indicators of performance under parole supervision such as employment activity, changes in residence, program participation, drug testing dates and results, supervision level changes, technical violation activity, field and collateral interactions, and violations and sanctions (including electronic monitoring assignments).

The method for developing the re-assessment instrument was the same as with the initial risk assessment instrument. Potential static and dynamic risk factors from both OTIS and FLOID were examined via multivariate logistic regression analysis to predict the probability of arrest for a new offense while under parole supervision. Table 2 below presents the 6 static and 4 dynamic risk factors included on the risk re-assessment model.

Table 3. Risk Re-Assessment Logistic Regression Model: The 10 Risk Factors of Arrest for a New Offense

Variables	Variable Description	B	S.E.	Sig.	Odds Ratio
Static Factors:					
AGE_SENT	Age at Sentencing	-.044	.01	.00	.96
PROPERTY	Most Serious Offense Was Property (yes/no)	.230	.09	.01	1.26
DRUGS_S	Most Serious Offense Was Drug Sales (yes/no)	.469	.12	.00	1.60
P_INCAR	# Prior Juvenile & Adult Incarcerations	.240	.03	.00	1.27
PARPROB	Prior Parole or Probation Revocation (yes/no)	.513	.10	.00	1.67
MHEALTH	History of Mental Health Treatment (yes/no)	.218	.11	.05	1.24
Dynamic Factors:					
EMPDAYS	# of Days Employed While on Parole	-.001	.00	.00	.99
RESIDS	# Residences While on Parole	.219	.03	.00	1.25
DRUG2	Proportion of Drug Tests With Positive Results	.467	.13	.00	1.60
TATTENDS	# of Months Attending Program(s) While on Parole	-.019	.01	.00	.98
Constant		.174	.23	.00	1.19

67% of the cases were correctly classified by the model (arrested vs. not arrested)

Interpretation of the Risk Assessments

The popularity of logistic regression rests on its ability to provide two useful pieces of information to policy-makers. First, the equation identifies the impact of significant predictors on the outcome. This information is gleaned from the sign (+/-) of the regression coefficient (column “B” in Tables 2 and 3). Predictors with a positive sign (such as prior incarcerations) indicate variables that *increase* the likelihood of arrest. Predictors with a negative sign (age at sentencing) indicate variables that *decrease* the likelihood of arrest.

The logistic regression coefficient (B) is in a scale of "log odds," making a direct interpretation impossible. However, a mathematical transformation (inverse of the natural log) of the coefficient provides the user with an "odds ratio" – a cornerstone of logistic regression interpretation. An odds ratio indicates the increase or decrease in the likelihood (odds) of the outcome (arrest) for each unit increase in the predictor variable. For example, the odds ratio of 0.96 for age at sentencing in both assessments indicates that for each additional year of age there is a 4% decrease in the likelihood of arrest (a parolee 30 years of age at sentencing is 40% less likely to be arrested than a parolee who is 20 at sentencing). In Table 3, the odds ratio of 1.6 for "most serious offense was drug sale" indicates that a drug sale offender is 60% more likely to be arrested while on parole than parolees convicted of other offenses.

Individual Prediction

Using the logistic regression models, the influence of individual factors on the probability of the outcome can be illustrated by solving the following equation:

$$\text{probability of arrest} = e^{\text{logit}} \,/\, (1 + e^{\text{logit}})$$

where the "logit" is the linear regression equation:

$$(\text{logit} = B_o + B_1x_1 + B_2x_2 + \ldots B_kx_k)$$

and x_1, x_2, ... x_k are the statistically significant predictor variables.

In the model described in Table 3, a Georgia parolee's probability of arrest can be calculated as:

$$\text{probability of arrest} = e^{\text{logit}} \,/\, (1 + e^{\text{logit}})$$

$$\begin{aligned}\text{where logit} = {} & .174 - .044(\text{AGE\_SENT}) + .230(\text{PROPERTY}) \\ & + .469(\text{DRUG\_S}) + .240(\text{P\_INCARS}) \\ & + .513(\text{PARPROB}) + .218(\text{MHEALTH}) \\ & - .001(\text{EMPDAYS}) + .219(\text{RESIDS}) \\ & + .467(\text{DRUG2}) - .019(\text{TATTENDS})\end{aligned}$$

For a sample case, OTIS and FLOID data provide the actual values for the ten factors in the re-assessment. Our sample parolee is a 25 year-old property offender[1] (burglar) with one prior incarceration, a prior parole revocation, a history of mental health treatment, while on parole was employed for 180 days, lived in 3 residences, had 50% of drug tests positive and attended programs for 9 months. His probability of arrest for a new offense while on parole supervision is .82 (on a scale of 0 – 1, which can be interpreted as an 82% chance of arrest while on parole):

Sample Case z = .174 - .044(25) + .230(1) +.469(0) + .240(1) + .513(1) + .218(1) - .001(180) + .219(3) + .467(.50) - .019(9).

Sample Case Probability of Arrest = .82

Initial assessment risk scores for individuals entering parole are computer-generated by the Parole Board Research Unit and supplement the information currently available to parole officers from the *Thelma Lou* reporting system. As parole activity is accumulated in FLOID, risk re-assessment scores are computer generated and officers are notified of risk level changes through e-mail (See Chapter 4 which describes the test for this process).

General Prediction

Our analysis confirms what we are learning from parole officers and chiefs in the field: (a) the importance of community supervision performance, (b) the pay-off (in terms of reduced recidivism) for keeping a parolee employed and in programs, and (c) the cumulative negative influence of drug use and residential instability.

The Importance of Parole Performance

This project is the first in Georgia to statistically demonstrate the important role dynamic risk factors play in determining success under supervision. While traditional risk assessments focus on offender characteristics (age of on-set) and prior criminal history, our re-assessment model demonstrates the importance of performance in the community and how parole behavior directly influences risk of re-offending.

Those factors that predict a parolee's liklihood of recidivating on the first day under supervision (youth, being a property or drug offender, having a prior record, and having mental health problems) are exacerbated among those parolees who perform poorly during parole supervision. Since the dynamic factors continually change during the course of parole, the probability of arrest must be continually recalculated (at on-going or regularly scheduled re-assessment intervals). For example, the probability of arrest for a 20-year old property offender with a prior probation revocation is 25%; but if one half of his drug tests are positive, his probability of arrest increases to 48%.

[1] Dichotomous predictor variables are all coded 0 or 1, where 0=no and 1=yes.

The Pay-Off of Jobs and Programs

The Parole Board's current emphasis on employment and treatment programs is soundly justified. The analysis of Georgia parolees indicates that the pay-off for each day of employment during parole is a 1% reduction in the likelihood of arrest. That translates into a 30% decrease in the likelihood of arrest for only one month (30 days) of employment. A parolee employed for a year is 3.5 times less likely to be arrested than a similarly situated parolee who is unemployed for the year.

Similarly, each month of attending programs during parole results in a reduction of 2% in the likelihood of arrest. That translates into a 24% decrease in the likelihood of arrest for one year (12 months) of programming. A next step in this on-going project is to refine the measurement of program participation – to determine the relationship between the type of program and the days of attendance per month and the pay-off in reduced recidivism. This is only possible by improving the current measurement of program participation in FLOID, including the refinement of tracking daily attendance in program types within the four program tracks (substance abuse, cognitive skills, education and employment).

The Negative Influence of Drug Use and Residential Instability

This analysis demonstrates the negative influence of drug use and residential instability during parole supervision. The drug test factor (proportion of drug tests that are positive) is an extremely important factor. For each incremental change in the ratio (positive to total tests), there is a 60% increase in the likelihood of arrest. That translates into increasing the odds of arrest by almost 20 times if a parolee moves from one-third of his drug tests returning positive to one-half of his drug tests returning positive.

The importance of drug test failures as an indicator of risk highlights a series of issues. First, 28% of the study cohort had no drug tests recorded. Only one-third of the study cohort had any positive drug tests (ranging from 4% to 100% of their tests returning positive, with an average of 18%). In other words, there are few instances of parolees with exceptionally high levels of drug test failures (such as the 50% indicated in the illustration above). However, if drug test failures are a strong indication of risk, it would appear compelling to conduct a higher rate of drug testing among parolees.

Finally, there is a 25% increase in the likelihood of arrest each time a parolee changes address. That translates into doubling the odds of arrest by simply moving three times while on parole (having four residences). This significant relationship was uncovered only after extensive manual cleaning of the residential records in FLOID for the parolees in the study cohort. This leads us to conclude that not only innovative analysis but also the basic need to improve data quality is critical to good risk assessment. Records of parolee residence must be improved if this information is to be incorporated successfully into an "automated" system of calculating risk. Since undertaking this project, officers have worked to improve residential record keeping. As they receive feedback from their FLOID data entry (such as automated risk scores), their motivation for improving data quality increases. Today's FLOID data is significantly cleaner than even the data of one year ago.

In order to determine how well the new risk assessment instruments *perform* (differentiate between those who get arrested from those who do not), we apply the assessment instruments to the cohort under study. This step allows for a comparison of the instrument's predictions to actual parolee outcomes. Since all parolees in the study cohort completed parole, *we know* whether or not they were arrested for a new offense while on parole.

We begin by dividing the estimation sample into ten groups of similar size defined by their predicted risk level (10% of the sample falls into each risk level). These groups are then assigned a predicted risk level from 1 to 10, referred to as "deciles of risk." For example, group 1 (lowest risk) has a predicted probability of arrest from 0 to .24. Figure 1 presents the proportion of parolees in the estimation sample that were actually arrested for a new offense while on parole by the 10 predicted levels of risk for each assessment. As the predicted probability of arrest increaseed (risk increases from 1 to 10), the proportion of offenders arrested also increaseed (from 21% to 74% on the initial assessment and from 18% to 78% on the re-assessment). This provides evidence of each model's ability to correctly classify a parolee as either "low" or "high" risk.

The 10 risk levels in Figure 1 were then grouped into low, medium, and high risk levels in Figure 2. The cut points for each level were placed where noticeable stepping points emerged on the 1 to 10 scale and where the 3-level classification would produce groups of the same size. Similar to Figure 1, as the *predicted* probability of arrest increased (from low to high) the proportion of parolees *actually* arrested also increased (from 26% among the low risk group to 69% among the high risk group). The initial assessment places 30% of all parolees into the "high risk" category, while the re-assessment places 37% of all parolees into the "high risk" category.

Figure 1. Percent of Estimation Sample Arrested for a New Offense by Risk Level 1-10

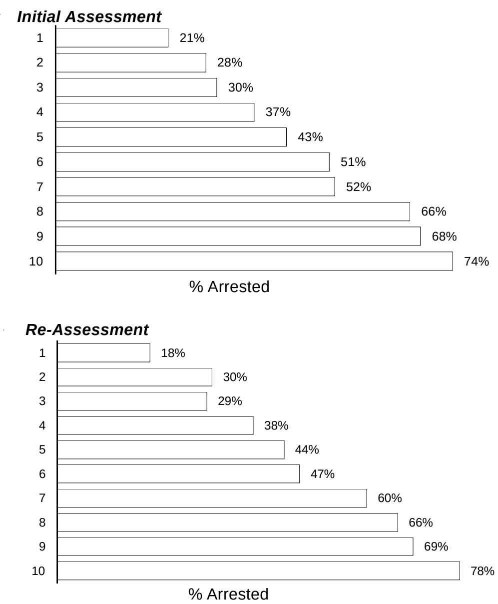
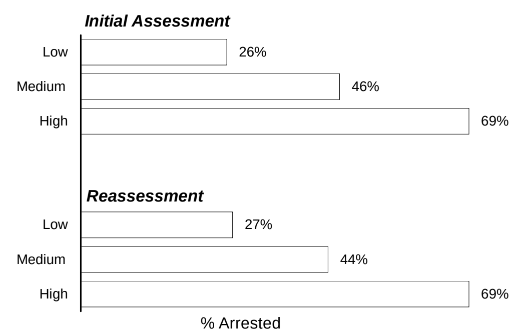


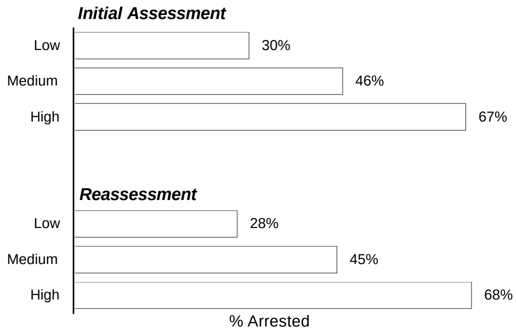
Figure 2. Percent of Estimation Sample Arrested for a New Offense by Risk Level



Validating the Instruments on a New Georgia Parolee Sample

Once the risk assessment models were completed, they were applied to a new group of parolees – the "validation" sample. Validation studies predict arrest activity on a different set of cases (those *not* used in developing the models). The predictions can then be compared to the actual case outcomes, since all validation sample parolees completed their parole (like the estimation sample, we know whether or not they were arrested while on parole). Figure 3 presents the percent of parolees in the validation sample that were arrested for a new offense while on parole, shown by their predicted risk level (risk levels are defined by the same predicted probability of arrest as those in Figure 2).

Figure 3. Percent of Validation Sample Arrested for a New Offense by Risk Level



The collapsed three risk levels for the validation sample (low, medium, high) in Figure 3 reflect predictions consistent with the estimation sample. As the predicted probability of arrest increased, the actual proportion of offenders arrested also increases (from 28% to 68%). This exercise provides the second level of validation of each model's ability to classify a parolee as either "low" or "high" risk.

How Do Our Instruments Compare to the LSI?

In order to make statements about the quality of a statistically-derived risk assessment instrument, scientists rely on a number of techniques. Statistical measures of *goodness of fit* indicate that our model does a good job of describing the outcome (getting arrested). Yet policy-makers making choices among competing methods of assessing risk want to know which assessment instrument does better than its competitors. To examine this issue, we selected a number of objective means for comparing our newly created risk assessments to others used in the field of parole decision-making.

Our Risk Scales are Correlated with Arrest Behavior

Quantifying the relationship between a risk scale or assessment instrument and an outcome of interest (in this case, arrest behavior) is possible with the Pearson correlation coefficient. Research indicatse that the LSI-R has a moderate correlation with outcomes of interest. Correlations between the LSI-R and recidivism (new arrest or re-incarceration) have been reported to range from r=.13 among female offenders (Doudy, 2002), to r=.26 (Lowenkamp, 2001; Motick, 1992) and r=.51 (Coulson, 1996) among male offenders. Doudy et al. (2002) document a *typical* correlation of around r=.40.

Comparing our models to this benchmark, we find that both our initial risk assessment and re-assessment instruments perform *as well as* the LSI-R. Correlations between the automated risk assessments and the outcome (arrest while on parole) varied from r=.35 for the initial instrument to r=.38 for the re-assessment instrument.

Our Risk Scales Correctly Classify Parolees

The percentage of cases that are *correctly classified* by the statistical model is an important benchmark used in selecting among competing combinations of risk factors in the development of a logistic regression risk scale. A comparison is made between a simple classification or binary prediction for each case (the parolee is predicted to be arrested or not) and the actual outcome for each case (the parolee was actually arrested or not). If we predicted each parolee in the study correctly, we would correctly classify 100% of the cases.

Our automated risk assessment models correctly classify 65% of the cases on the initial assessment and 67% of the cases on the re-assessment. In comparison, Motick (1992) reports the LSI-R can correctly classify 62% of cases and the self-report LSI can correctly classify 52% of cases under study.

Our Risk Scales Identify High Risk Offenders

Finally, one benchmark we set for our own model development process was the ability to correctly identify *high risk* offenders. As shown in Tables 2 and 3, between 67% and 69% of the offenders that we predicted to be high risk were actually arrested. This is over twice the arrest rate among those we predict to be low risk. In comparison, Coulson (1996) reports recidivism of 30% for offenders defined as high risk with the LSI-R , and Lowenkamp (2001) reports a 57% rate of recidivism for offenders defined as high risk with the LSI-R.

Chapter 4: Implementation

As the development phase of the risk assessment project comes to an end, implementation becomes the priority. The automated initial risk assessment instrument went into the field Spring 2001 to replace the paper-and-pencil form. ARS conducted numerous seminars during 2001 and 2002 to inform Parole Board management, Regional Directors, and Parole Chiefs about the instrument, its development, and how it can be used. Currently, the Parole Board Research Unit executes the initial risk assessment program on all new parolees as they enter the statewide caseload. As described in Chapter 2, that instrument accesses data stored in the corrections prisoner database. Parole officers run a simple report in *Thelma Lou* on new parolees coming onto their individual caseloads for the initial risk level score. In some parole field offices, Chiefs or administrative staff run the risk reports for the officers. The risk assessment information does not dictate a parolee's level of supervision, but provides the officer with a statistical gauge of the parolee's risk of arrest for a new offense while on parole. The officers use the information, as they would any other pertinent data, when assigning a parolee's first supervision level.

The initial risk assessment went to the field in Spring 2001.

Feedback on the initial risk instrument has generally been positive. During the summer of 2001 we visited several parole field offices across the state to learn more about how the initial risk instrument was working in the field, to hear suggestions for improving the instrument, and also to learn new ideas for implementating the re-assessment instrument. Chiefs who regularly use the instrument report that officer decisions matched the instrument recommendations 75%-80% of the time, with much of the variation stemming from boot camp and sex offender parolees who have mandated levels of supervision regardless of risk assessment results. Many officers have expressed satisfaction with the elimination of the time-consuming paper forms, and there is a sense that the new instrument is a valuable tool when making supervision decisions. The format and delivery of the instrument also has received wide support and approval.

The Current Re-Assessment Test Pilot

Test piloting the risk re-assessment instrument in the field began in early 2003. While much time was dedicated during the development phase to making the instrument user-friendly, the pilot is necessary to assess the instrument's performance, and to acquire firsthand feedback from the field about its efficacy and functionality. Forty-nine parole officers representing each of the six parole regions are currently testing the re-assessment instrument.

Test piloting of the re-assessment instrument began early 2003.

The re-assessment pilot is designed to mimic the continual flow of operational information *from* and *to* the field. Every evening, updated case management information from each parole officer's laptop is uploaded to the central office mainframe computer in Atlanta. As described in Chapter 2, the results of the re-assessment instrument can change daily, as dynamic risk information is updated daily on parolee performance. Therefore, each night the computer program on the re-assessment instrument is executed on all current parolees. If a parolee on a test pilot caseload crosses over the "high risk" threshold (becomes high risk or drops out of high risk), an e-mail message is automatically generated and sent to the supervising officer advising him/her of the change in risk status. The e-mail identifies the parolee and includes the factor(s) that led to the change in risk level (such as a failed drug test or change in residence). Officers are then able to make adjustments to the supervision level, if deemed necessary. Notification of a risk level change does not require a change in case supervision.

Survey of Test Pilot Participants

Prior to statewide deployment of the automated risk re-assessment instrument into the field, a survey will be e-mailed to all test pilot participants to gather detailed information on the performance of the re-assessment instrument. The objective of the survey is to obtain as much information as possible about the officers' confidence in the re-assessment results, the notification system, training issues, and other information pertinent to a statewide deployment of the instrument. The survey results will be carefully reviewed and suggestions for changes in the process will be considered. The main goal of the pilot project is to adjust the project implementation plans to better serve the needs of the parole officers.

Statewide Parole Officer Training

Statewide training on both assessment instruments will begin May 2003. All parole officers and chiefs will attend a four-hour training session that will review the development of the instruments, the notification system, and how officers are to use the new information being provided. Three training sessions will be conducted that each include field personnel from two regions. The training initiative will be completed by June 2003, followed by full implementation of the automated re-assessment instrument in all regions.

Following implementation, officers will be encouraged to provide continuing feedback on its performance and utility. During the statewide training sessions, officers will be given contact information for ARS and encouraged to communicate any problems or concerns. All feedback will be reviewed with Parole research staff and project changes will be made as needed.

Continued Validation Is Essential

After the instruments are fully implemented in the field, ARS will then begin to focus on a new validation study. As discussed in Chapter 3, the assessment instruments were developed on a cohort of actual Georgia parolees, and were then tested on a second "validation" sample of Georgia parolees. However, demographic changes in the offender population as well as changes in offending patterns over time can cause substantial changes in the parolee population, which in turn can lead to changes in the applicability and weights of the current risk factors. Continual validation studies on new cohorts of Georgia parolees are therefore critical to ensure the validity of the risk instruments. It is possible that over time new factors will become statistically predictive of arrest behavior, and some of the current risk factors may no longer be significant. ARS is currently working with the Parole Board to develop a continued validation study design.

The Next Step: Defining Parole Success

The next phase of the risk assessment project will focus on the development of a mechanism for the on-going measurement of parole "success." Using the same data that was used to develop the risk instruments, ARS will investigate relationships between static and dynamic predictor variables (demographics, offense, risk assessments, treatment plan, parole performance) and parole success. The project will involve an extensive analysis of all available outcome measures to develop a composite measure of success, which will likely be a summary measure of multiple indicators. An attempt will be made to answer such questions as:

- Who succeeds on parole, and why?
- How does program participation affect successful outcomes?
- Can the make-up of the parole population affect success across officers, offices, and regions?

With each parolee's case classified as "successful or not" for purposes of the study, a summary index of success can be created and calculated for each officer, office, and region to allow for a comparison of relative success across the state. This will allow for the identification of best practices, identification of potential treatment plan or execution problems, the identification of potential problem populations, as well as inform resource allocation. By analyzing the relationship between risk, parole performance, and case outcomes, the Parole Board will ultimately be in a position to determine, among similar risk level offenders, the treatment strategy that leads to higher levels of success on parole.

Bibliography

Andrews, D.A. & Bonta, J. (1995). Manual for the LSI-R: The Level of Service Inventory-Revised. Toronto, Ont: Multi-Health Systems, Inc.

Ashford, J. & LeCroy, C. (1988). Predicting Recidivism, An Evaluation of the Wisconsin Juvenile Probation and Aftercare Risk Instrument. *Criminal Justice and Behavior,* 15, 141-151.

Austin, J. & Litsky, P. (1982) Identifying Absconders from Parole and Probation Supervision: An Evaluation of Nevada's Risk Screening Instruments. San Francisco: National Council on Crime and Delinquency.

Austin, J., Litsky, P., McCarthy, D. (1989) A Validation Assessment of the District of Columbia's Department of Corrections Community Risk Instrument. San Francisco: The National Council on Crime and Delinquency.

Bonham, G., Janeksela, G., Bardo, J., Iacovetta, R. (1984). Predicting Parole Outcome Via Discriminate Analysis. *Justice Quarterly,* 1, 329-342.

Bonta, J. & Motiuk, L.L. (1985). Utilization of an Interview-Based Classification Instrument: A Study of Correctional Halfway Houses. *Criminal Justice and Behavior,* 12, 333-352.

Bonta, J. & Motiuk, L.L. (1987). The Diversion of Incarcerated Offenders to Correctional Halfway Houses. *Journal of Research in Crime and Delinquency,* 24, 302-323.

Bonta, J. & Motiuk, L.L (1990). Classification to Halfway Houses: A Quasi-Experimental Evaluation. *Criminology,* 28, 497-506.

Bonta, J. & Motiuk, L.L (1992). Inmate Classification. *Journal of Criminal Justice,* 20, 343-353.

Bonta, J. (1989). Native Inmates: Institutional Response, Risk, and Needs. *Canadian Journal of Criminology,* 49-62.

Bonta, J., Pang. B., Wallace-Papretta, S. (1995). Predictors of Recidivism Among Incarcerated Female Offenders. *The Prison Journal,* 75, 277-294.

Brennan, T. & Oliver, W.L. (2002). Evaluation of the Reliability and Validity of COMPAS Scales: New York Probation Sample. Traverse City, MI: Northpointe Institute for Public Management, Inc.

Brennan, T. & Oliver, W.L. (2001). Evaluation of the Reliability and Validity of COMPAS Scales: National Aggregate Sample. Traverse City, MI: Northpointe Institute for Public Management, Inc.

Brennan, T. & Wells, D. (1997). A Test of the Northpointe COMPAS Risk Assessment on New Jersey Parolee Offenders. Traverse City, MI: Northpointe Institute for Public Management, Inc.

Copas, J.B. & Marshall, P. (1998). The Offender Group Reconviction Scale: A Statistical Reconviction Score for use by Probation Officers. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 47, 159-171.

Cottle, C., Lee, R., Heilbrun, K. (2001). The Prediction of Criminal Recidivism in Juveniles, A Meta-Analysis. *Criminal Justice and Behavior,* 28, 367-394.

Coulson, G., Ilacqua, G., Nutbrown, V., Giulekas, D., Cudjoe, F. (1996). Predictive Utility of the LSI for Incarcerated Female Offenders. *Criminal Justice and Behavior,* 23, 427-439.

Dowden, C. & Andrews, D.A. (1999). What Works for Female Offenders: A Meta-Analytic Review. *Crime and Delinquency*, 45, 438-452.

Dowdy, E.R., Lacy, M.G., Unnithan, P. (2002). Correctional Prediction and the Level of Supervision Inventory. *Journal of Criminal Justice,* 30, 29-39.

Funk, Stephanie J. (1999). Risk Assessment of Juveniles on Probation – A Focus on Gender. *Criminal Justice and Behavior*, 26, 44-68.

Gendreau, P., Little, T., Goggin, C. (1996). A Meta-Analysis of the Predictors of Adult Offender Recidivism: What Works! *Criminology,* 34, 575-607.

Gottfredson, S.D. & Gottfredson, D.M. (1985). Screening for Risk Among Parolees: Policy, Practice, and Method. *Excerpt from: Prediction in Criminology,* 54-77.

Hanlon, T., O'Grady, K., Bateman, R. (2000). Using the Addiction Severity Index to Predict Treatment Outcome Among Substance Abusing Parolees. *Journal of Offender Rehabilitation*, 31, 67-79.

Harm, N.J. & Phillips, S.D. (2001). You Can't Go Home Again: Women & Criminal Recidivism. *Journal of Offender Rehabilitation*, 32, 3-21.

Jung, S. & Rawana, E., (1999). Risk and Need Assessment of Juvenile Offenders. *Criminal Justice and Behavior,* 26, 69-89.

Kirkpatrick, B. (1999). Exploratory Research of Female Risk Prediction and LSI-R. *Corrections Compendium,* 24, 1-17.

Kirkpatrick, B. (1998). A Study of Offenders Under Intensive Community Supervision. *Perspectives,* 24-28.

Kroner, D. & Mills, J. (2001). The Accuracy of Five Risk Appraisal Instruments in Predicting Institutional Misconduct and New Convictions. *Criminal Justice and Behavior*, 28, 471-489.

Loucks, A. & Zamble, E. (1999). Predictors of Recidivism in Serious Female Offenders – Canada Searches for Predictors Common to Both Men and Women. *Corrections Today*, 26-32.

Lowenkamp, C., Holsinger, A., Latessa, E. (2001). Risk/Need Assessment, Offender Classification, and the Role of Childhood Abuse. *Criminal Justice and Behavior,* 28, 543-563.

Loza, W. & Loza-Fanous, A. (2001). The Effectiveness of the Self-Appraisal Questionnaire in Predicting Offenders Post-Release Outcome. *Criminal Justice and Behavior,* 28, 105-121.

Loza, W. & Simourd, D.J. (1994). Psychometric Evaluation of the Level of Supervision Inventory (LSI) Among Male Canadian Federal Offenders. *Criminal Justice and Behavior,* 21, 468-480.

Morgan, Kathryn D. (1994). Factors Associated With Probation Outcome. *Journal of Criminal Justice*, 22, 341-353.

Motiuk, L.L., Bonta, J. & Andrews, D.A. (1986). Classification in Correctional Halfway Houses. The Relative and Incremental Predictive Criterion Validities of the Megargee-MMPI and LSI Systems. *Criminal Justice and Behavior,* 13, 33-46.

Motiuk, M.S., Motiuk, L.L. & Bonta, J. (1992). A Comparison Between Self-Report and Interview-Based Inventories in Offender Classification. *Criminal Justice and Behavior,* 19, 143-159.

Motiuk, M., Motiuk, L., Bonta, J. (1992). A Comparison Between Self-Report and Interview-Based Inventories in Offender Classification. *Criminal Justice and Behavior,* 19, 142-159.

Olson, D., Lurigio, A., (2000). Predicting Probation Outcomes: Factors Associated with Probation Rearrest, Revocations, and Technical Violations During Supervision. *Evaluation and Program Planning*, 13, 399-406.

Quinsey, V.L., Harris, G.T., Rice, M.E., & Cormier, C.A. (1998). Violent Offenders: Appraising & Managing Risk. Washington DC: American Psychological Association.

Sims, B. & Jones, M. (1997). Predicting Success or Failure on Probation: Factors Associated with Felony Probation Outcomes. *Crime and Delinquency,* 43, 314-327.

Smith, W. & Aloisi, M. (1999). Prediction of Recidivism Among “Second Timers” in the Juvenile Justice System: Efficiency in Screening Chronic Offenders. *American Journal of Criminal Justice,* 23, 201-222.

Tollett, C. & Benda, B. (1999). Predicting “Survival” in the Community Among Persistent and Serious Juvenile Offenders: A 12-Month Follow-Up Study. *Journal of Offender Rehabilitation,* 28, 49-76.

Werner, E., & Palmer, T. (1976). Psychological Characteristics of Successful and Unsuccessful Parolees: Implications of Heteroscedastic and Nonlininear Relationships. *Journal of Crime and Delinquency,* 165-178.

Wheeler, G. & Hissong, R. (1990). Transferability of Probation Risk-Assessment Instruments: A Case for Caution. *Evaluation and Program Planning*, 13, 399-406.

Wright, K., Clear, T., Dickson, P. (1984). Universal Applicability of Probation Risk-Assessment Instruments. *Criminology,* 22, 113-134.

Zimmerman, S., Martin, R., Rogosky, T. (2001). Developing a Risk Assessment Instrument, Lessons About Validity Re-Learned. *Journal of Criminal Justice,* 29, 57-66.