Developing profiles of violent offenders and Identifying groups of violent offenders at high risk of recidivism and treatment failure

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Executive Summary

Offenders who are convicted of violent crimes are often sentenced to probation (Greenfeld, 1996). Probation officers assess the risk that offenders will commit a new violent crime or any crime while on probation to determine the extent of supervision and the conditions of probation. Probation departments generally categorize offenders as low, medium, and high risk, with each level of risk corresponding to a more intensive monitoring strategy. For example, violent offenders assessed as high risk may be placed on specialized or intensive supervision probation. The specialized probation may require probationers to have two office contacts with their probation officer per month, to allow the officer to visit and search their home once a month at an unannounced time, to submit to random drug and alcohol testing, to abide by a curfew, to have no contact with the victim, and to participate in treatment. Offenders assessed as medium and low risk may be placed on standard probation and the low risk offenders compared to the medium risk offenders will have fewer face-to-face contacts with their probation officer and fewer probation conditions. Thus, the probation officers' risk assessments are designed to prevent additional violent behavior and assist in more efficient allocation of the resources used to monitor violent offenders.

The following report examines and develops profiles of violent offenders sentenced to probation across the state of Illinois. It identifies groups of violent offenders who are at a high risk of recidivism and treatment failure. The data used come from a 2000 data collection effort by the Illinois Criminal Justice Information Authority (ICJIA) in collaboration with the Administrative Office of the Illinois Courts (AOIC).

Chapter 1 examines whether violent adult probationers differ from other probationers, and if so, in what ways. Using the entire sample of 3,364 discharged probationers, we compare the 1,385 violent offenders to the 1,959 other offenders on their criminal histories, offense characteristics, substance abuse, and mental health characteristics, court imposed conditions, and arrests and probation discharge status. Violent offenders had more previous drug and property arrests, more prior convictions and more prior probation sentences than the other offenders did. Violent offenders and other offenders had the same basic need of better employment opportunities and job skill training, though a greater percentage of violent offenders needed to obtain their high school diploma. Over a third of the probationers in each group were identified as having a history of alcohol abuse and about 44% of the offenders in each group were identified as having a history of illicit drug abuse. These findings indicate that substance abuse is a problem for both types of probationers. Violent offenders were more likely to be noncompliant with treatment, and a significantly higher percentage of violent offenders (six percentage point difference) have non-traffic new arrests while on probation, and one or more technical violations of probation. The study examines whether violent offenders are significantly different from other probationers, which has implications for whether the limits to participation in selected community based treatment programs often imposed on violent offenders should be reassessed.

This study also examines domestic violence offenders as a subset of violent offenders since over 300 of the violent offenders discharged from probation were convicted of domestic battery. In section 2 of chapter 1, the 637 domestic violence offenders were examined to determine whether the 202 domestic batterers that had children living with them differ from the 344 domestic batterers that did not have children living with them. The discharged domestic violent probationers with or without children did not differ on the variables studied. The court also did not appear to require such offenders with children to adhere to more stringent conditions than those required for domestic violent offenders without children.

Several studies indicate that a significant proportion of domestic violence cases involve illicit drug use or abuse. Prior studies of incarcerated domestic batterers indicate that 24% of batterers reported using illicit drugs alone, or more commonly, in combination with alcohol at the time of the offense (Greenfield et al., 1997) and that 22% reported a history of illicit drug addiction (Bergman & Brismar, 1994). In section 3 of chapter 1, we explore differences in the profiles of illicit drug users and non-users, domestic violence offenders and other violent offenders, and the profile of illicit drug users who were also domestic violence offenders. Domestic violence offenders were more likely than other violent offenders to be older, to have parented children, to have children living with them, and to be employed. Illicit drug users, on the other hand, were more likely than non-drug users to have incomes below the poverty level, to be unemployed, to not be currently married and to have less than a high school education. Illicit drug users had more extensive criminal histories than non-drug using offenders and committed a wide variety of crimes. Domestic violence offenders and other violent offenders had similar criminal histories and drug using domestic violent offenders did not differ in their criminal history from the other three groups. Significant interaction effects were found for only a few variables most notable in weapon use and in court ordered conditions. Drug users were also more likely to have community service ordered, but drug-using domestic violence offenders were less likely to have community service orders than the other three groups. Similarly, drug-using domestic violence offenders were 2.2 times more likely to have restitution ordered, 1.6 times more likely to be ordered to pay fines and 2.6 times more likely to have mental health treatment ordered than all other offenders. Judges imposed more conditions on this subgroup than on any other, suggesting that judges may be aware of the dangers that this group poses. Domestic violence offenders who were also illicit drug users were far more likely to have used a weapon and to have spent time in jail while on probation than other offenders. These interaction effects support previous research that indicates that perpetrator drug use increases the risk of serious violence to intimate partners (Wilson et al., 2000).

The dropout rates for court mandated treatment range between 25 to 52 percent (Chalk & King, 1998; Gondolf, 1997), indicating that a significant proportion of domestic batterers do not take advantage of the treatment that is being offered. Chapter 2 examines how best to combine significant predictors of whether domestic batterers fail to complete domestic batterer treatment. Of the 355 domestic batterers on probation who were court mandated to participate in domestic violence treatment, 31.8% failed to complete treatment. Two predictors, whether a generalized aggressor, which is an offender who batterers both family members and non-family members, and whether the court ordered substance abuse treatment are strong predictors of treatment failure. These predictors have received only limited investigation in previous research. Our study indicates that high school dropouts that are ordered to undergo substance abuse treatment are at a very high chance of treatment failure, which is defined as being prematurely terminated or refusing to attend domestic violence treatment. Unemployed generalized aggressors also have a high chance of treatment failure. Classification tree analysis compared to logistic regression showed substantially better accuracy at classifying treatment failures.

Chapter 3 employs classification tree analysis to address whether three groups of violent offenders have similar or different risk factors for violent and general recidivism while on probation. A sample of 1384 violent offenders on probation was classified as generalized aggressors (N = 308), family only aggressors (N = 332), or non-family only aggressors (N =

744). The strongest predictor of violent recidivism while on probation was whether the offender was a generalized aggressor or not, with generalized aggressors more likely to be arrested for new violent crimes. The total number of prior arrests predicted violent recidivism for generalized aggressors, but did not significantly predict violent recidivism for family only and non-family only aggressors. For all three groups of violent offenders, treatment noncompliance was an important risk predictor of violent and general recidivism. The implications for the risk assessment and domestic violence literature are discussed throughout this report.

Chapter 1: Profiles of Violent Offenders

Introduction

Criminology and criminal justice, not to mention the general public, has always shown an interest in violent crime and the violent offender. The criminological literature in particular evidences this focus in various theoretical approaches to violence and violent offenders (See for example, Spencer, 1966, Wolffgang, 1969 ; Mulvihill and Tumin, 1969; Katz,1988, Bell and Bennett, 1996, Zimring, 1998 Riedel and Welsh, 2002). The criminal justice literature approaches the issue from a more practical standpoint, seeking ways to deal with the violent offender (President's Commission on Law Enforcement and Administration of Justice, 1967; National Commission on the Causes and Prevention of Violence, 1977, Wilson, 1995, Schmalleger, 1999). While the criminal justice approaches to dealing with the violent offender deal with both adults and juveniles, adult violent offender programming tends more to incarceration and post incarceration programming.

Pre-incarceration programs especially probation for violent adults focus on felony offenders and not specifically for violent offenders (Petersilia, 1997). Juvenile violent offender programs, on the other hand, reflect an emphasis on keeping the violent offender in the community (Fagan, 1990, Champion, 2001). There is a dearth of literature on violent adult offenders on probation. One of the more comprehensive reviews of probation research literature (Perersilia, 1997) has limited discussion of violent offenders on probation except to note that they are often excluded from intermediate sanctions and other community-based programming except for intensive supervision probation. A recent article by Olson and Stalans (2001) does focus on violent offenders on probation but limits its focus to comparing domestic violence offenders to other violent probationers.

Most studies examining the predictors of violent recidivism while violent offenders are serving a probation sentence have concentrated on domestic batterers (e.g., Aldarondo & Sugarman, 1996; Bennett, Goodman, & Dutton, 2000; Kropp & Hart, 2000; Goodman, Dutton, & Bennett, 2000; Shepard, 1992). The current study takes a broader approach and seeks to examine whether violent adult probationers differ from other probationers and if so in what ways. This broader approach adds to the literature addressing whether criminal offenders specialize in committing certain crimes or whether criminal offenders participate in a wide range of criminal activity. Prior research has drawn mixed conclusions on whether criminal offenders are specialists or generalists. In a study comparing arrested burglars and arrested violent offenders, Farrington and Lambert (1994) concluded that “while there was a great deal of versatility in offending, there was also some specialization, since half of the burglars had a previous conviction for burglary and half of the violent offenders had a previous conviction for violence. Other research also has found evidence of specialization, though the majority of violent offenders are generalists (Farrington, Snyder, & Finnegan, 1988; Lattimore, Visher, & Linster, 1995; Osgood, Johnston, O’Malley, & Gachman, 1988; Simon, 1997; Weiner, 1989). When nonviolent and violent offenders are compared, studies have concluded that most violent offenders do not exclusively or consistently limit their criminal activity to violent crimes (Holland & McGarvey, 1984) and have a similar criminal background as repeat nonviolent offenders (Capaldi & Patterson, 1996). Piquero (2000) corrected design limitations in previous studies and compared frequent nonviolent offenders to frequent violent offenders. He found that frequent violent offenders are quite similar to frequent nonviolent offenders.

Studies examining specialization issues have used prospective designs or sample of arrestees. The primary objective of the current research was to address whether probation departments should have specialized units to supervise violent offenders. Thus, we limited our focus to nonviolent and violent offenders on probation and addressed several practical questions. Compared to probationers arrested for only nonviolent crimes, do probationers arrested for violent crimes (violent probationers): (a) have different needs, (b) have significantly different criminal histories, (c) receive different court imposed conditions, and (d) have different outcomes?

Methodology

Data for this study were obtained from a survey of Illinois adult probationers discharged from probation during a four week period in November and December, 1997 and yielded data on a total of 3,364 probationers, The survey was conducted by the Illinois Criminal Justice Information Authority in collaboration with the Probation Division of the Administrative Office of the Illinois Courts. Unlike crime and most other criminal justice data, there appeared to be no seasonality associated with this discharge data. (For a detailed review of survey methodology sees Adams, Olson and Adkins, 2002). Probation officers, referred back to their case files, and completed the survey on the probationers' information such as basic demographics plus substance abuse and criminal history, offense characteristics, sentencing and court imposed conditions, and case outcomes. All sections of the state, urban, suburban, and rural, were represented. Illinois Criminal History Record Information (CHRI) or "rap sheets", which trained research assistants coded, provided prior criminal history measures and measures of the rate of new offenses while on probation and six months after probation was completed.

Definition of Violent Probationers

Research often identifies violent offenders based on the type of offense for which the probationer is currently on probation (current offense). While this is a good starting point, it is inadequate in our view, in two ways. The current offenses included as “violent” are often limited to the more traditional offenses such as homicide, robbery, assaults, batteries, and sexual assaults. Many other current offenses that have either obvious (e.g. aggravated arson) or hidden (e.g. violation of an order of protection) violent aspects to them should be included in the list of violent current offenses.

The second way the designation of violent offenders based on current offense is inadequate is that it does not take into account prior criminal history, particularly, prior arrests for violent offenses. A probationer on probation for burglary, for example, could have had a prior arrest for a violent offense and, as such could legitimately be designated a violent offender. Criminal history information was obtained from Illinois Department of State Police “rap sheets” by Authority staff and made available for this study.

With these prior limitations in mind, we reviewed the offense data from the survey and identified 37 violent offenses. The definition of violent offender used in this study included those offenders whose current offense is identified as violent or any offender who has a history of any violent offenses as identified through rap sheet analysis. Offenses that qualified as violent crimes included: First and second degree murder, involuntary manslaughter, reckless homicide, armed or unarmed robbery, aggravated battery, battery, reckless conduct, domestic battery, aggravated assault, aggravated arson, aggravated unlawful use of weapon, unlawful use of weapon, unlawful use of weapon by felon, aggravated discharge of a firearm, harassment, mob action, intimidation, unlawful restraint, violation of an order of protection, and violation of an Illinois Bail Bond.[iii] Attempted crimes for these offenses as well as specific versions of these offenses such as those against a police officer or child were also included.[iii] The most frequent current offenses were domestic battery (N = 311) and some form of battery (including aggravation, N = 190), with 52.1% of the violent probationers placed on probation for a misdemeanor crime and the remainder placed on probation for a felony including six offenders serving probation for some form of homicide. In addition, offenders placed on probation for criminal damage to property against an intimate adult partner or family member were included as violent offenders because such charges are common part of domestic violence offenses. Similarly, offenders charged with a probation violation against an adult family member or intimate partner were included as violent offenders. The number of discharged probationers designated as violent offenders using the above criteria totaled 1,385. Other offenders designated as "non-violent offenders" in this report totaled 1,948 for total sample size of 3,333 discharged probationers.

Findings

Chi-square analyses were performed to examine the bi-variate relationships. It should be noted that one characteristic of the Chi Square statistic is that large samples may yield significant differences even when the actual differences expressed in percentages are small. Because of this we elected establish the following guidelines for designating a relationship as significant: Differences in percentages must exceed five percent and probability levels (p values) must be at least .001. Later analyses will explore differences in probation outcomes using multivariate logistic regression analyses.

Demographic variables

Violent and non-violent offenders differed on four of the five static demographic characteristics found in Table 1.1. Although the two groups did not differ on average age (violent offenders, 31.9; non-violent offenders 30.3) significantly fewer of the violent offenders on probation (14.4%) were under age 21 than was the case for the other probationers (25.2%). This finding does not support the public's view that violent offenders are young teenagers. While the vast majority of discharged probationers in both groups were male, significantly fewer violent offenders (13.6%) than other probationers (25.7%) were female. This is consistent with most profiles of female offenders.

Table 1.1. Comparison of Violent and Non-violent offenders Discharged from Probation on Demographic Characteristics

Demographic Characteristic	Violent Offenders (valid percentages)	Non-violent offenders (valid percentages)
Age*		
Under 21	195 (14.4%)	468 (25.2%)
21-30	475 (35.2%)	600 (32.3%)
31-40	410 (30.3%)	429 (23.1%)
Over 40	271 (20.1%)	358 (19.3%)
Female Probationers*	186 (13.6%)	495 (25.7%)
Race*		
African/American	536 (38.7)	590 (30.3%)
Hispanic	192 (13.9%)	261 (13.4%)
White	632 (45.6%)	1064 (54.6%)
Marital Status at Intake		
Divorced/Separated/Widowed	256 (19.8%)	321 (17.8%)
Married/Remarried	316 (24.5%)	375 (20.8%)
Never Married	718 (55.7%)	1106 (61.4%)
Number of Children Parented*		
None	559 (47.1%)	993 (59.2%)
One	255 (21.5%)	298 (17.8%)
Two or More	374 (31.5%)	386 (23.0%)

*$p < .001$

As shown in Table 1.1, a significantly higher percentage of the violent offenders compared to non-violent offenders were African-Americans. A final demographic difference between the two groups was that more of the violent offenders (53.0%) than other offender (40.8%) had parented children. Violent and non-violent offenders did not differ on marital status.

Social Status and Mental Health Adjustment

The percentages and frequencies of eight characteristics of social status or mental health adjustment are described in Table 1.2. Violent and non-violent offenders were similar on six of the eight characteristics that were measured at the intake interview and differed only on educational status and prior psychiatric treatment.

Violent offenders differed from non-violent offenders on educational status and prior psychiatric treatment. Almost half (48.0%) of the violent offenders had not completed high school whereas this was the case for a little over a third (38.5%) of the non-violent offenders. The vast majority of probationers in both groups did not have a history of psychiatric treatment, but slightly more of the violent offenders (16.4%) than non-violent offenders (11.1%) did so.

Violent and non-violent offenders had similar financial needs. About 60% of both groups were employed either full time or part time, but income levels were low. About a third of the probationers were making $5000 or less annually.

Over two-thirds of the probationers in both groups did not have children living with them at time of intake. This percentage was reduced to approximately 50% for female probationers in both groups, indicating that childcare is a key factor for female probationers. Finally, the great majority of both types of offenders were living with family or friends at intake. These findings suggest that the basic needs of these probationers as reflected in employment and income are the same for both violent and other probationers.

Table 1.2 Comparison of Violent and Other Probationers Discharged from Probation on Social and Mental Health Status

Social and Mental Health Status	Violent Offenders (Valid Percentages)	Non-violent offenders (Valid Percentages)
Employment Status at Intake		
Employed Full or Part time	789 (60.0%)	1126 (60.9%)
Unemployed/Looking	411 (31.2%)	547 (29.6%)
Out of Labor Force/Student	116 (8.8%)	175 (9.5%)
Income at Intake		
$5,000 or less	374 (34.1%)	517 (32.7%)
$5,000-$10,000	119 (10.8%)	201 (12.7%)
$10,001- $14, 999	165 (15.0%)	249 (15.7%)
$15,000-$19,999	144 (13.1%)	215 (13.6%)
$20,000-$24,999	109 (9.9%)	133 (8.4%)
$25,000-$29,999	66 (6.0%)	79 (5.0%)
$30,000 or more	120 (10.9%)	189 (11.9%)
Living Alone	221 (17.4%)	300 (16.5%)
Gang Member	94 (8.2%)	86 (5.2%)
Number of Children Living With Probationer		
None	780 (66.7%)	1153 (69.8%)
One	163 (13.9%)	224 (13.6%)
Two or More	226 (19.3%)	276 (16.7%)
Educational Status at Intake*		
No High School Diploma	588 (48.0%)	674 (38.5%)
High School or GED	473 (38.6%)	759 (43.4%)
Some College	164 (13.4%)	316 (18.1%)
Alcohol Abuse		
No	664 (61.0%)	963 (64.3%)
Yes	424 (39.0%)	535 (35.7%)
Illicit Drug Use		
No	783 (57.0%)	1079 (55.8%)
Yes	590 (43.0%)	854 (44.2%)
Prior Psychiatric Treatment*		
No	1021 (83.6%)	1528 (88.9%)
Yes	201 (16.4%)	190 (11.1%)

*$p < .001$

Measures of social and mental health adjustment were limited to self-reports of having a history of alcohol or illicit drug abuse and whether or not the offender had a history of psychiatric treatment. More in-depth information is often not found in probation files. As shown in Table 1.2, a little over one third of the probationers in each group had a history of alcohol abuse. Around 43% of offenders in each group had a history of drug abuse. One might have expected a higher percentage of non-violent offenders than violent offenders to have a history of illicit drug abuse since over a third of the other probationers were convicted of drug offenses. These findings indicate that drug abuse is a problem for both types of probationers. The drug of choice in both groups was primarily marijuana with drugs other than marijuana taken by only a fifth of offenders in both groups. These findings do not support the media's characterization of violent offenders as "crack heads" led into violence by crack cocaine.

These findings indicate that offender needs are remarkably similar in both groups particularly in regards to employment and substance abuse. On the other hand, violent offenders on probation compared to non-violent offenders on probation tended to be older, African-American and Caucasian men who had not completed high school.

Criminal History

Prior criminal history measures were created from coding the rap sheets. These data were incomplete in that data were missing on approximately 23% of the cases. No demographic or offense characteristic were significant predictors of whether a rap sheet was available or not. In a logistic regression, three variables were significant predictors, but only explained 7% of the variance and less than one percent of those who did not have a rap sheet were accuracy classified. Offenders on standard probation were less likely to have a rap sheet, offenders who used marijuana or both marijuana and illicit hard drugs were more likely to have a rap sheet, and those classified as a violent offender were more likely to have a rap sheet. It is our belief that the pattern of findings on criminal history variables reported here would not be essentially altered were complete data available, given the unpredictability of who had a rap sheet missing.

There were statistically significant differences between the violent and other probationer on five of the six criminal history variables. Table 1.2 presents the frequencies and valid percentages within each group on all of the criminal history measures. A much higher percentage of violent offenders (61.6%) than non-violent offenders (19.5%) had a history of three or more prior arrests, and non-violent offenders were more likely to have no prior arrests. Because prior arrests for violent offenses were included in the definition of a violent offender, this definition may contribute to the difference between the groups. When we examine only the cases that had no prior arrests for violent crimes, the difference observed at 3 or more prior arrests disappears (violent, 11.7%; other, 19.5%) and the relationship at no prior arrests also becomes less dramatic and reverses (violent = 52.1%, non-violent = 38.2%), X^2 (3) = 15.99, $p < .001$. This is more realistic since it is reasonable to expect that many probationers in both groups would have a prior arrest history.

Findings also indicate that violent offenders do not restrict their offending to violent offenses. As shown in Table 1.3, a significantly higher percentage of violent offenders had at least one prior arrest for a drug offense and had at least one prior arrest for a property crime. Violent offenders on probation were much more likely to have a history of two or more prior convictions (33.2%) than non-violent offenders on probation (11.1%). The majority of probationers in both groups had not been on probation before. However, violent offenders on probation were also significantly more likely to have been on probation two or more times before. Overall, these findings indicate that the violent probationers studied here had a more extensive criminal history than non-violent probationers.

Table 1.3 Comparison of Violent and Non-Violent Probationers on Criminal History Variables

Criminal History Variables	Violent offenders Valid Percentages	Non-violent offenders Valid Percentages
Total Prior Arrests*		
None	111 (9.2%)	399 (38.2%)
One	176 (14.6%)	279 (26.7%)
Two	174 (14.5%)	163 (15.6%)
Three or More	741 (61.6%)	204 (19.5%)
Prior Drug Arrests*		
None	807 (66.9%)	1024 (81.3%)
One	209 (17.3%)	147 (11.7%)
Two	98 (8.1%)	56 (4.4%)
Three or More	92 (7.6%)	33 (2.6%)
Prior Property Arrests*		
None	651 (54.0%)	947 (75.3%)
One	253 (21.0%)	191 (15.2%)
Two	109 (9.0%)	66 (5.4%)
Three or More	192 (15.9%)	53 (4.2%)
Prior DUI Arrests		
None	1095 (90.8%)	1127 (89.4%)
One or more	111 (9.2%)	143 (10.6%)
Total Prior Convictions*		
None	521 (43.6%)	740 (70.6%)
One	278 (23.2%)	192 (18.3%)
Two	171 (14.3%	67 (6.4%)
Three or More	226 (18.9%)	49 (4.7%)
Prior Adult Probation Sentences*		
None	643 (53.8%)	784 (74.8%)
One	332 (27.8%)	183 (17.5%)
Two	133 (11.1%)	54 (5.2%)
Three or More	88 (7.4%)	27 (2.6%)

*$p < .001$

Offense Characteristics

The specific offense characteristics examined compared the two groups on offense class, whether or not a weapon was used and specific victim variables including the number, age and gender of victims and the relationship of the offender to the victim. Finally, we examined differences in initial risk classification. With the exception of victim age, there were significant differences between the two groups on all of the offense characteristics. The vast majority of victims in both groups were adults (violent group, 81.1%; other group 82.6%).

The majority (54.1%) of violent offenses were misdemeanors and the majority (52.5%) of the other offenses were felonies, X^2 (2) = 23.86, p < .001. This is likely due to a number of factors. The number of serious violent offenses (e.g. murder, robbery, assault) was small. Also, domestic battery which had the highest frequency within the violent offense group is a Class A misdemeanor unless certain conditions are met.[iv] On the other hand, many property offenses and drug offenses that have high frequencies within the other offense group are felonies. Even when classification of violent offenses is restricted to the more traditional listing than the one we have used in this study, the percentage distribution remains in the same direction, that is the majority of violent offenses are misdemeanors. An additional observation is that the Court is often reluctant to grant probation to violent felony offenders. As we note later in this report, this should be considered when excluding "violent offenders" from participation in various community programs.

In the vast majority of offenses a weapon was not used but violent offenders were more likely to use a weapon (24.6%) than were non-violent offenders (1.9%), X^2 (1) =388.15, p < .001. Violent offenders were much more likely to have one or more victims in their current offense (53.0%) than was the case for non-violent offenders (15.0%), X^2 (3) = 591.92, p < .001. Most offenses involved only one victim. While about a third (34.6%) of the victims of non-violent offenders were female, two-thirds (66.7%) of the victims of violent offenders were female, X^2 (2) = 106.92, $p < .001$. This gender difference may reflect the substantial proportion of domestic violence offending.[v] Interestingly, a much higher percentage of other offenses involved both male and female victims (21.7%) than was the case (3.6%) of violent offenses. A substantially higher percentage of violent offenders (60.7%) were involved in a domestic relationship with the victim than was the case (12.1%) for non-violent offenders, X^2 (1) 163.71, $p < .001$. Finally, violent offenders were more likely (65.4%) than non-violent offenders (30.4%) to be initially classified as maximum risk and only 6.2% of violent offenders compared to 20.2% of non-violent offenders were classified as minimum risk, X^2 (2) = 323.6, $p < .0001$. This is partly due to a common practice of automatically classifying offenders with a current violent offense as maximum risk because of the offense, but also due to the differences in offense characteristics and criminal history of the violent offenders.

Sup*ervision Strategies and Court –Ordered Conditions*

A number of options are available to the court in addition to placing an offender on probation. Many probation orders have special conditions attached that require the probationer to pay restitution, pay probation fees, pay court costs, participate in drug screening (urinalysis), participate in a variety of treatment programs, serve specific number of hours in community service, and observe a curfew. In addition, the probationer may be assigned to a variety of specialized caseloads that provide special services and heightened supervision not usually provided under standard probation.

Chi-square analyses found statistically significant differences between violent and non-violent offenders on five of the ten measures representing court ordered conditions. Not surprisingly, a higher percentage of violent offenders (24.4%) were assigned to specialized caseloads (intensive probation or domestic violence units) than was the case for non-violent offenders (8.2%), X^2 (3) = 256.49, p < .001. Interestingly, only 88 non-violent offenders (5.2%) were assigned to specialized DUI or drug caseloads despite the fact that 56.6% of non-violent offenders were convicted of either DUI or drug offenses. However, 30.8% of non-violent offenders compared to 24.9% of violent offenders were required to participate in drug screening (urinalysis), X^2 (1) = 13.01, p < .001, and 50.5% of non-violent offenders compared to 39.5% of violent offenders were ordered into substance abuse treatment, X^2 (1) = 39.21, p < .001. Though both violent and non-violent offenders had a similar need, the court was more likely to order substance abuse treatment and urinalysis for non-violent offenders.

The court probably did not have information about substance abuse and illicit drug use of many violent offenders because treatment evaluations are often not used at the sentencing stage. The difference in court ordered substance abuse and urinalysis occurs because of lack of information and the court's reliance on the convicted offense. Overall, however, significantly more of the violent offenders (64.1%) than non-violent offenders (54.8%) were ordered into some type of treatment X^2 (1) = 28.64, p < .001; this difference reflects the fact that 29% of the violent offenders were ordered into domestic violence treatment.

Violent and non-violent offenders received similar court orders to pay restitution, court costs and probation fees. Restitution was part of the probation order in about 20% of the cases in both groups. Seventy percent in both groups were required to pay supervision fees and 52% in both groups were required to pay court costs. Interestingly, 54.2% of the non-violent offenders compared to 48.6% of violent offenders were assessed fines, X^2 (1)= 9.69, p < .003. Employed non-violent offenders compared to employed violent offenders were more likely to receive fines, with a difference of 11 percentage points. When the current offense was a misdemeanor, 79.3% of employed non-violent offenders were assessed a fine compared to 68% of employed violent offenders, X^2 (1) = 15.41, $p < .001$. When the current offense was a felony, 58.3% of non-violent employed offenders compared to 47.6% of violent employed offenders were assessed a fine, X^2 (1) = 6.5, $p < .01$. There were no significant differences between the groups when the offenders were unemployed, $p < .23$.

Overall, 23.9% of non-violent offenders and 19.3% of violent offenders were ordered to perform community service, which is not a statistically significant difference. From a practitioner's view, however, the court is often reluctant to order community service for violent offenders so we further explored this possibility. Both non-violent and violent offenders who committed a misdemeanor offense had a similar likelihood of receiving a community service order. However, when the current offense was a felony, 32.2% of non-violent offenders compared to 22.4% of violent offenders received a community service order, X^2 (1) = 12.4, $p < .001$. This difference was stable across employment status and relationship of the offender to the victim. There also was a difference between violent offenders and non-violent offenders based on geographical location. In suburban areas surrounding the Chicago area, 48.3% of non-violent offenders were ordered to complete community service whereas only 24% of violent offenders received this order, X^2 (1) = 14.97, $p < .001$. About 22% of both non-violent and violent offender groups in rural areas and in Cook County received community service. Thus, violent offenders received differential treatment and were less likely to receive community service orders if they lived in the suburban areas surrounding Chicago or committed a felony. Finally, in both groups curfew was ordered for approximately four percent of the offenders.

These findings indicate that the Court does impose different conditions for violent offenders, most notable the likely assignment of violent offenders to specialized caseloads, and some type of treatment. On the other hand, the Court in suburban areas is more reluctant to order community service for violent offenders. Moreover, substance abuse treatment and screening are more likely to be imposed on non-violent offenders, even though violent and non-violent offenders have a similar need for such conditions. A substantial percentage of violent offenders were ordered into substance abuse treatment, but judges should apply such conditions similarly to violent and non-violent offenders.

Probation Outcomes

To what extent do violent offenders differ from other probationers on probation outcome? Are violent offenders less successful on probation than non-violent offenders and if so in what ways? Probation outcomes such as technical violations and filing of a Violation of Probation Petition (VOP) are not pure measures of probationers' noncompliance; these measures also reflect probationer officers' discretionary decision making. Typically, probation officers first provide informal warnings and then may file a VOP for more persistent noncompliance.

We first used Chi-Square analyses to examine probation outcomes. Table 1.4 presents the frequencies and percentages within the violent offender and non-violent offender samples on 14 probation outcomes. Table 1.4 shows that violent offenders and non-violent offenders differed on 6 of the 14 probation outcomes. A greater percentage of violent offenders (46.5%) than non-violent offenders (39.2%) received one or more technical violation during supervision. As noted above, the groups did not differ on the reason for such violations such as drug use, missed appointments or nonpayment of fees. However, of those offenders ordered into any type of treatment, 32.1% of violent offenders (32.1%) and 21.1% of non-violent offenders received technical violations for noncompliance with treatment orders. The samples of violent and non-violent offenders also differed on arrests rates while serving their probation sentence. Violent offenders were more likely to have an arrest for a non-traffic crime (6% point difference), an arrest for any new crime (10% point difference), and an arrest for a violent crime (10% point difference). While almost half of the violent offenders were arrested for a crime including traffic offenses, only 18% of the violent offenders were arrested for a new violent crime while on probation. These findings suggest that most violent offenders are not a threat to public safety.

Moreover, we conducted a chi-square analysis controlling for whether offenders had no prior arrests or at least one prior arrests to determine if the differences in arrest rates disappeared when criminal history was controlled. The chi-square was significant for both the first time offender comparison and the experienced offender comparison on whether a violent crime was committed while serving the probation sentence: 20.7% of first time violent offenders compared to 9% of first time non-violent offenders and 17.6% of experienced violent offenders compared to 7.3% of experienced non-violent offenders, $p < .001$. Within the first time offender group, violent and non-violent offenders had similar arrest rates for non-traffic offenses (violent = 23.3%, non-violent = 20%) and for any new crime while on probation (violent = 40.5%, non-violent = 36.3%), $p < .40$. Within the experienced group, violent offenders while on probation were more likely to commit a non-traffic crime (31.6%) than were non-violent offenders (26.4%), X^2 (1) = 8.7, $p < .002$. Within the experienced group, violent offenders also were more likely to commit any new crime while serving their probation sentence (49.5%) than were non-violent offenders (39.2%), X^2 (1) = 29.78, $p < .0001$. Thus, these findings suggest that experienced violent offenders are more likely to commit crimes while on probation than are

Table 1.4. Comparison of Violent and Other Probationers Discharged from Probation

Probation Outcomes

Probation Outcomes	Violent Offenders (Valid %)	Non-violent Offenders (Valid %)
Discharge Status		
Positive	807 (65.0%)	1229 (69.6%)
Negative	435 (35.0%)	536 (30.4%)
Probation Revoked	199 (16.2%)	273 (15.7%)
Administrative Sanctions Used	128 (9.8%)	209 (11.3%)
Petitions to Revoke Probation Filed*	456 (32.9%)	526 (27.0%)
Number of Technical Violations*		
None	697 (53.5%)	1115 (60.8%)
One	341 (26.2%)	430 (23.5%)
Two	131 (10.1%)	149 (8.1%)
Three or more	133 (10.2%)	139 (7.6%)
Technical Violation Drug Use	112 (8.1%)	169 (8.7%)
Technical Violation Missed Appointments	243 (17.5%)	304 (15.6%)
Technical Violations Nonpayment of Fees	219 (15.8%)	320 (16.4%)
Technical Violations Noncompliance with Treatment*	285 (32.1%)	225 (21.1%)
Any New Arrest While on Probation*	671 (48.8%)	734 (38.6%)
Non-Traffic Arrests While on Probation*	400 (31.0%)	452 (25.1%)
New Arrest for Violent Crime While on Probation*	246 (17.9%)	145 (7.6%)
Six Month Post Discharge Arrests	201 (16.7%)	177 (14.1%)
Days in Jail While on Probation		
None	1018 (80.9%)	1492 (84.1%)
Up to a Month	119 (9.5%)	158 (8.9%)
Between One and Two Months	46 (3.7%)	44 (2.5%)
Between Two and Three Months	25 (2.0%)	31 (1.7%)
More Than Three Months	51 (4.1%)	50 (2.8%)

*$p < .001$

experienced non-violent offenders whereas first time violent and non-violent offenders have similar arrest rates.

Given that violent and non-violent offenders differed on demographics and criminal history, it is necessary to test whether the statistically significant differences on probation outcomes are spurious and due to criminal history, demographic or offense characteristics. Table 1.5 presents logistic regressions on non-traffic arrests, any new arrest, and new arrests for violent crimes while offenders were serving their probation sentence. The numbers under the "b" column represent unstandardized logistic coefficients and the odds ratio is presented in parentheses. Initial logistic regressions tested all variables using stepwise procedure. We then conducted a second logistic regression that used force entry to enter all significant variables from the stepwise procedure in order to reduce the number of missing cases and to check on moderating effects. In all models we controlled for total number of prior arrests because it was significantly related at the bivariate level and the violent and non-violent offender groups had different prior arrest histories. To reduce missing cases, we used median substitution on the total number of prior arrest variable. Preliminary analyses using the original prior arrest predictor did not differ substantially from the analyses presented in Table 1.5 and 1.6.

As shown in Table 1.5, even after controlling for significant demographic, background, offense, and criminal history predictors, violent offenders are significantly more likely to have a new arrest for a non-traffic crime and a new arrest for a violent crime. Controlling for other characteristics reduced, but did not eliminate the difference in arrest rates. On the comparison of any new arrests, including traffic offenses, while on probation, the difference between violent and non-violent offenders is almost eliminated.

Table 1.5. Logistic Regression Predicting New Arrests While on Probation

Predictors	Non-Traffic New Arrests		Any New Arrests		New Arrests for Violence	
	b	Odds Ratio	b	Odds Ratio	b	Odds Ratio
Income Level	-.10	(.90)***	-.09	(.92)***	-.12	(.89)**
Offender's Age	-.02	(.98)***	-.03	(.97)***	.50	(1.66)**
Education Level	-.44	(.64)***	-.53	(.59)***	-.45	(.63)**
Never Married	.56	(1.74)***	.34	(1.41)**		
Male Offender			.39	(1.47)**		
Race (African American)						
Caucasian Offender			-.63	(.54)***		
Hispanic Offender			-.79	(.45)***		
Other Race			-.50	(.60)		
County (Rural is Baseline)						
Suburban Area	-.25	(.77)				
Urban Area	.31	(1.37)*				
Chicago/Cook	.24	(1.27)				
Drug Use (None is baseline)						
Marijuana only	.35	(1.42)**	.28	(1.33)*		
Harder Illicit drugs	.48	(1.62)*	.71	(2.03)***		
Marijuana and Hard Illicit Drugs	.66	(1.93)***	.78	(2.19)***		
Used a Weapon					.58	(1.79)**
Prior Psychiatric Treatment	.33	(1.38)*				
Number of Treatments Ordered			.21	(1.23)**		
Gang Membership (None)						
Gang Member	1.08	(2.94)***	1.03	(2.81)***		
Unknown whether Gang Member	.69	(1.98)***				
Total prior arrests	.04	(1.05)***	.06	(1.06)***	.02	(1.02)
Initial Risk Assessment						
Maximum vs. Medium/Low					.64	(1.90)***
Specialized Supervision					.54	(1.71)**
Violent vs. Non-violent Offender	.25	(1.28)*	.20	(1.23)[a]	.58	(1.79)**
Constant	-1.15		.27		-2.30	
Model X^2	276.83***		448.27***		135.92***	
Total Sample Size	2004		2188		1900	

Superscript symbols indicate two-tailed probability level: * < .05, ** < .01, *** < .001, **a** = .052;

Information in parentheses by the Predictor Category indicates the baseline value.

The first column of Table 1.6 presents the unstandardized coefficients from the ordinary least squares regression predicting number of technical violations. The second column of Table 1.6 presents the unstandardized coefficients and in parentheses the odds ratio of the logistic regression model predicting whether a violation of probation petition was filed. The last column of Table 1.6 presents the logistic regression model predicting treatment noncompliance, which was conducted using only offenders who were ordered to participate in some kind of treatment. Treatment noncompliance was defined as not showing up for treatment, premature termination by the therapist for failure to comply with rules, and voluntarily dropping out of treatment. We conducted these analyses in the same manner as described above. As shown in Table 1.6, after controlling for significant demographic, background, offense and criminal history predictors, violent and non-violent offenders did not significantly differ on number of technical violations, whether a violation of probation petition was filed or treatment noncompliance. This finding suggests that violent offenders and non-violent offenders are similar on their tendency to comply or not comply with probation conditions and/or receive similar discretionary sanctions from criminal justice professionals.

Table 1.6. OLS and Logistic Regressions Predicting Number of Technical Violations, Whether a VOP is filed and Treatment Noncompliance

Predictors	Number of Technical Violations	Filed a Violation of Probation Petition		Treatment Noncompliance	
	B	b	Odds Ratio	b	Odds Ratio
Income Level	$-.04^{***}$	-.11	$(.90)^{***}$	-.11	$(.89)^{***}$
Offender's Age	$-.01^{***}$	-.02	$(.98)^{***}$	-.02	$(.97)^{**}$
Education Level	$-.22^{***}$	-.47	$(.63)^{***}$	-.44	$(.65)^{**}$
Male Offender				.48	$(1.61)^{**}$
Race (African American)					
Caucasian Offender		-.46	$(.63)^{***}$		
Hispanic Offender		-.38	$(.69)^{*}$		
Other Race		-.87	(.42)		
County (Rural is Baseline)					
Suburban Area	$.39^{***}$	.74	$(2.09)^{***}$	.78	$(2.19)^{***}$
Urban Area	$.14^{*}$	.24	(1.28)	.20	(1.22)
Chicago/Cook	$-.16^{**}$	-.01	(.99)	.47	$(1.59)^{**}$
Taken Illicit Drugs	$.24^{***}$				
Drug Use (None is baseline)					
Marijuana only				.60	$(1.82)^{***}$
Harder Illicit drugs				.24	(1.27)
Marijuana and Hard Illicit Drugs				.30	(1.36)
Used a Weapon					
Number of Treatments Ordered	$.20^{***}$	.51	$(1.67)^{***}$	.65	$(1.91)^{***}$
Gang Member	$.29^{***}$				
Unknown whether Gang Member	$.34^{***}$				
Total prior arrests	.02			.01	(1.01)
Specialized Supervision	$.23^{***}$				
Violent vs. Non-violent Offender	-.003	.06	(1.06)	.23	(1.25)
Constant	.83	-.05		-1.85	
R^2	$.16^{***}$				
Model X^2		196.33^{***}		143.64^{***}	
Total Sample Size	2004	2306		1416	

Superscript symbols indicate two-tailed probability level: $^{*} < .05$, $^{**} < .01$, $^{***} < .001$, $^{a} = .052$;

Information in parentheses by the Predictor Category indicates the baseline value.

Summary and Conclusions

This study compared violent and non-violent probationers on 44 variables in 6 categories, and found that violent and non-violent probationers had statistically significant differences on 22 of these measures. While one can conclude from these findings that violent probationers do indeed differ from other probationers, some differences are more important than others. Overall, violent and non-violent offenders appeared to have the same basic needs for better employment opportunities so that they are not living in poverty, though violent offenders were more likely to be a high school dropout.

Similarly, both types offenders had a similar history of substance abuse, particularly drugs, but the court was more likely to mandate substance abuse treatment and random drug screening as probation conditions for non-violent offenders. Though a substantial percentage of violent offenders (40%) were ordered into substance abuse treatment and one-quarter were mandated to participate in random drug screening, judges need to order the necessary drug abuse screenings so that differential treatment can be eliminated.

Violent offenders compared to non-violent offenders also were less likely to have community service as part of their probation order when sentenced by a suburban court or when they committed a felony. These findings have policy implications. Community service sends the important message that the offender has offended against and harmed society not only the individual victim. Previous research also found that judges were less likely to sentence domestic batterers compared to other violent offenders to community service (Olson & Stalans, 2001). Thus, it appears that judges require education on their tendencies to provide differential treatment and the reasons why this differential treatment is inappropriate.

Not surprisingly, one key area of difference was in criminal history. Violent offenders had a greater number of previous arrests, convictions and probation sentences than the non-violent offenders. A greater percentage of violent offenders compared to non-violent offenders also had a prior arrest for a property crime and a prior arrest for a drug crime. Consistent with previous research (e.g., Farrington et al., 1988; Lattimore et al., 1995; Simon, 1997; Weiner, 1989), this finding suggests violent offenders on probation do not specialize in committing only violent crimes, but participate in a wide range of criminal activity. Our research extends the literature on specialization by examining a large representative sample of violent and non-violent probationers. Studies on specialization have often used prospective designs with young children or samples of arrestees. By focusing on only probationers, we are able to address whether violent and non-violent offenders who serve their sentence in the community have different risks and needs. The criminal history data suggests that violent probationers are more likely to have prior experience with the criminal justice system.

One of the more important areas of comparison is on probation outcomes. The key observation in this regard is that violent probationers and non-violent probationers have similar outcomes on following probation conditions and receiving sanctions for noncompliance. The major difference was that violent offenders were more likely to be arrested for a non-traffic crime or a violent crime while serving their probation sentence. Moreover, violent and non-violent offenders who had at least one prior arrest for any crime differed on arrest rates for non-traffic offenses whereas violent and non-violent offenders who were first time offenders had similar rates for non-traffic crimes while on probation. Violent and non-violent offenders did not differ on arrest rates for the six months after their probation discharge.

Probation programs that automatically exclude violent offenders from participation might want to review their policies in light of the low rate of violent offending while on probation. Moreover, specialized programs have been created to supervise violent offenders and often determine eligibility by the current convicted offense. These specialized programs cannot be justified by the needs or risk of noncompliance with probation orders. Violent and non-violent offenders had similar needs such as better employment and substance abuse treatment and monitoring as well as similar risk of committing technical violations. However, violent offenders compared to non-violent offenders did have a significantly higher arrest rate for non-traffic crimes and violent crimes while on probation, which may warrant more intensive monitoring. In the current research, it is noteworthy that 7.6% of the offenders classified as "non-violent" based on previous criminal history and current offense were arrested for violent crime while serving their probation sentence. Though violent offenders were defined as having either a prior arrest for a violent crime or being placed on probation for a violent crime, this definition did not capture all offenders who commit violent offenses. Probation programs should seriously reconsider the appropriateness of assigning offenders to specialized probation programs based on their current convicted offense. The extra resources that are required for specialized programs, moreover, cannot be justified by the substantially higher risk of violent offenders as a group. Resources may be better allocated to the development of risk assessment tools that provide accurate classification of an offender's risk of committing new crimes while on probation.

Section 2. Analyses of Domestic Violence Offenders With and Without Children

In this section, we compare two groups of offenders who were arrested for domestic violence: those living with children and those not living with children. We wanted to learn if they differ in any significant ways on social and criminal history measures and whether the court places more stringent conditions on domestic violence offenders with children. Research indicates that witnessing domestic violence between their parents (or caregivers) is a traumatic event for children and has the risk of injury during such events (Edleson, 1999). Witnessing domestic violence can and often does have both-short term and long-term effects on the child, including behavioral and emotional functioning and cognitive functioning and attitudes (Fantuzzo et al., 1997; Rossman, 1998; Jaff, Wilson & Wolf, 1986; Henning et al., 1996). Domestic violence incidences in families with children are different form those without children in that the children are at least secondary victims of these offenses. We wanted to explore whether the offenders were also different.

Domestic violence offenders were identified by both the current offense and by reference to prior history of domestic violence offenses. We selected a sub sample of 637 domestic violence offenders from the total sample of 3,364 probationers. Of this group, 202 had children living with them and 344 did not have children with them. Data were missing on 91 cases. Domestic violence offenders included those offenders placed on probation for domestic violence crimes that had no prior violent arrests or only prior arrests for domestic violence crimes; offenders placed on probation for a non-violent crime that had prior arrests for violent crimes only involving domestic violence; and offenders that had been arrested for both domestic violence and other violence based on criminal history and current offense. Current domestic violence crimes included those arrested for violation of an order of protection, for a violent crime against an adult former or current intimate partner, and those arrested for criminal damage to property against a family member because domestic batterers frequently commit this crime (Laviolett & Barnett, 2000). We compared domestic violence offenders living or not living with children on the same six categories of variables used in comparing violent and “other “ probationers.

Results

We compared the two groups on nine demographic variables. We found statistically significant differences between the domestic violent offenders with and without children on four of these variables. Most of these differences were consistent with a marital or intimate partner relationship in which children are present. For example, a significantly higher proportion of domestic violence offenders with children were 21 to 40 years of age than was the case for such offenders without children. More of the domestic violence offenders without children were under age 21. Parenting, even when distorted by domestic violence, is most frequently found in the 21 to 40-age range. A significantly higher percentage of domestic violence offenders with children were married or remarried, and a significantly higher percentage of those without children were living alone. Finally, a much higher percentage of domestic violence offenders living with children had parented children. As noted earlier, all of these findings are consistent with a marital or intimate partner relationship in which children are present. There were no statistically significant differences between domestic violence offenders living with children and those not living children on all of the remaining variables.

As noted earlier, we were particularly interested in examining differences between theses two groups with respect to court orders, especially whether such orders were more stringent for domestic violent offenders with children. We found no evidence that the court acts differently for either group. The only difference that approached statistical significance was whether any treatment was ordered and the finding is curious at best. More of the domestic violent offenders without children than those with children were ordered into some kind of treatment.

These findings clearly indicate that discharged domestic violence probationers who are or are not living with children do not differ at least on the variables studied. Moreover, judges do not appear to require offenders living with children to adhere to more stringent conditions

Chapter 2. Domestic Violence and Illicit Drug Use

Several studies indicate that a significant proportion of domestic violence cases involve illicit drug use or abuse. Prior studies of incarcerated domestic batterers indicate that 24% of batterers reported using illicit drugs alone or more commonly, in combination with alcohol at the time of the offense (Greenfield et al., 1997) and that 22% reported a history of illicit drug addiction (Bergman & Brismar, 1994). In a sample of male addicts, an early onset of drug/alcohol related problems and a history of only illicit drug use -- particularly cocaine -- were related to being a perpetrator of domestic violence (Bennett, Tolman, Rogalski, & Srinivasaraghavan, 1994). This study also found that drug abuse rather than alcohol abuse was more strongly related to domestic violence. Similarly a study utilizing self-report data from domestic violence victims also found that male partners' illicit drug use was a better predictor of woman abuse than was alcohol use (Kantor & Straus, 1989).

The use of illicit drugs also may change the nature and severity of the domestic violence. Illicit drug use by any member of the household is a risk factor for violent death of women in the home (Bailey, Kellerman, Somes, Banton et al., 1997). Another study also suggests that offenders abusing only illicit drugs may inflict more severe injuries than may offenders that abuse only alcohol (Roberts, 1988). This was confirmed by a more recent study (Wilson, et al., 2000) that found that physical abuse was significantly higher for women with perpetrators who used drugs only compared to those who used alcohol only.

The study presented here builds on previous research linking illicit drug use and domestic violence by exploring differences in the profiles of illicit drug users and non-users; domestic violence offenders and other violent offenders, and the profile of illicit drug users who were also domestic violence offenders. Using binary logistic regression, we explored differences in characteristics among these groups with particular interest in examining the interaction between drug use and domestic violence.

All of our analyses focus on the subset of probationers who were violent offenders. From the violent offenders we identified two specific types of offenders for this analysis: drug users and domestic violence offenders. The survey instrument recorded whether the probationer had used drugs at any time prior to intake, at intake, or never. We collapsed this into a dichotomous variable indicating illicit drug use or not, yielding a total of 587 drug users and 786 non-drug users. The definition of domestic violence was identical to that earlier described. There was a total of 640 domestic violence offenders with 308 generalized aggressors who committed violent crimes against both intimate partners and non-family members and 332 family only batterers who committed violent crimes against only family members. There were 744 non-family only violent offenders whose history did not include domestic violence offenses as defined earlier, and who committed violent crimes against only acquaintances and strangers.

Analysis involved comparing four groups: domestic violent offenders using illicit drugs, domestic violent offenders not using illicit drugs; other violent offenders using illicit drugs and other violent offenders not using illicit drugs. We elected to use binary logistic regression and the resultant odds ratios as indicators of the likelihood that any particular group's profile would include a specific characteristic or whether the groups did not differ on a particular characteristic. In addition, we were particularly interested in the interaction between drug use and domestic violence-seeking to learn the likelihood of various characteristics being part of the profile for those offenders who were both drug users and domestic violence offenders. We compared the groups on the same six categories of variables used in the previous studies.

RESULTS

Demographic variables and social/mental health

Table 2.1. presents the unstandardized b, odds ratio, and significance level for illicit drug users compared to non-drug users in the first column, the comparisons of domestic batterers to other violent offenders in column two and illicit drug using domestic batterers compared to the other groups in column three. The logistic regression tested the direct effect of illegal drug use, the direct effect of the type of violent offender (domestic violence or other violent) and the interaction between these two variables.

Table 2.1 Comparison of Illicit Drug Users and Domestic Violence Discharged Probationers on Demographic, Social and Mental Health Variables

Demographic Variables	Illicit Drug Users vs. Non-Drug Users			Domestic Violence Offenders vs. Other Violent Offenders			Illicit Drug Using-Domestic Violence Offenders		
	b	Odds Ratio	Sig.	b	Odds Ratio	Sig.	B	Odds Ratio	Sig.
Age	.05	1.1		.47	1.6	**	-.11	.90	
Gender	-.32	.73		.34	1.4		.49	1.6	
Race	-.05	.95		.08	1.1		-35	.70	
Income	.71	2.0	***	-.05	.96		-.26	.78	
Marital Status	-.68	.51	***	.27	1.3		.11	1.1	
Employment	-.50	.60	*	.33	1.4	*	-.26	.77	
Living alone	.01	1.0		.35	1.4		-.13	.88	
Education	-.68	.51	***	.25	1.3		-.18	.84	
Number of Children Parented	.18	2.0		.72	2.1	***	-.26	.77	
Number of Children Living With Probationer	.14	1.2		.55	1.7	**	-.51	.60	
Alcohol Abuse	1.1	3.0	***	-.12	.89		.64	1.9	
History of Psychiatric Treatment	.37	1.4		-.08	.93		.45	1.6	

*** p<.001, ** p<.01, * p<.05

Domestic violence offenders were more likely than other violent offenders to be older, to have parented children, to have children living with them, and to be employed. Illicit drug users on the other hand were more likely than non-drug users to have incomes below the poverty level, to be unemployed, to not be currently married and to have less than a high school education. Drug users were three times more likely to have alcohol abuse as part of their profile than non-drug users.

Criminal history

Table 2.2 presents the logistic regression results for criminal history variables. Offenders reporting illicit drug use were approximately two times more likely than other offenders to have one or more prior arrests for any crime, one or more prior arrests for a drug offense, for a violent offense and for a property offense. Similarly, illicit drug offenders were also 1.7 times more likely to have had prior convictions and to have been on probation at least once before. Clearly illicit drug users had more extensive criminal histories than all other offenders in the groups and did not commit only drug offenses.

Domestic batterers, however, were similar to other violent offenders in their criminal history and illicit drug using-domestic batterers did not have more extensive criminal histories than the other three groups.

Table 2.2. Comparison on Illicit Drug Users and Domestic Violence Discharged Probationers on Criminal History Variables.

Criminal History	Illicit Drug Users Compared to Non-Drug Users			Domestic Violence Offenders Compared to Other Violent Offenders			Illicit Drug Using-Domestic Violence Offenders		
	B	Odds Ratio	Sig.	b	Odds Ratio	Sig.	b	Odds Ratio	Sig.
Number of Prior Arrests	.94	2.5	**	-.04	.96		-.37	.69	
Number of Prior Drug Arrests	.96	2.6	***	-.18	.64		-.25	.78	
Number of Prior Violent Arrests	.71	2.0	*	-.14	.87		-.19	.83	
Number of Prior Property Arrests	.68	2.0	***	.10	1.1		-.50	.61	
Number of Prior Convictions	.55	1.7	*	.06	1.1		-.18	.84	
Number of Prior Probation Sentences	.53	1.7	*	-.01	.99		-.10	.91	
Number of Prior DU1 Arrests	.02	1.0		-.13	.88		-.02	.98	

*** P<. 001, ** p<. 01, * p<. 05

Offense characteristics

Table 2.3 presents the logistic regression results for offense characteristics. The key difference was that illicit drug users compared to non-drug users were more likely to be charged with a felony and to be classified as a maximum risk.

Domestic violence offenders differed significantly from other non-violent offenders on offense characteristics. Domestic violence offenders were far more likely than other offenders to have one or more victims, to have victims who were female and victims who were adults. Domestic violence offenders were also the most likely to have their offense classified as a misdemeanor but at the same time to be classified as a maximum risk.

Table 2.3: Comparison of Illicit Drug Users and Domestic Violence Discharged Probationers on Offense Characteristics.

Offense Characteristics	Illicit Drug Users Compared to Non-Drug Users			Domestic Violence Offenders Compared to Other Violent Offenders			Illicit Drug Using-Domestic Violence Offenders		
	b	Odds Ratio	Sig.	b	Odds Ratio	Sig.	b	Odds Ratio	Sig.
Number of Victims	-.23	.80		1.9	6.7	***	-.09	.92	
Gender of Victim	-.27	.77		2.0	7.3	***	-1.5	.86	
Age of Victim	1.9	6.7		1.0	2.8	*	2.0	.14	
Offense Class	-.72	.49	***	1.3	3.9	***	-.02	.98	
Risk Rating	.34	1.4	*	1.3	3.8	***	.01	.86	
Use of Weapon	-.53	.59		-.46	.63		1.0	2.8	***

*** p<.001, * p<.05

One important difference was in weapon use. There were no differences between drug users and non-drug users as well as domestic violence offenders and other violent offenders on weapons use. However, drug-using domestic violence offenders were 2.8 times more likely to have used a weapon than all other offenders examined. This supports previous research that indicates that illicit drug use is a factor that places domestic batterers at a higher risk to commit severe injuries to their partners, (Wilson, et al., 2000).

Supervision Strategies

Table 2.4 presents the logistic regression results showing significant differences between the groups in the type of supervision imposed and in the special conditions imposed as part of the probation order. In general, drug users and drug-using domestic violence offenders were more likely to have special conditions imposed than were the other groups. As shown in column one, illicit drug-using offenders were far more likely to have probation conditions of some kind of treatment ordered, urinalysis, community service, and drug treatment ordered.

Table 2.4. Comparison of Illicit Drug Users and Domestic Violence Discharged Probationers on Supervision Conditions Imposed by the Court.

Court Ordered Conditions	Illicit Drug Users Compared to Non-Drug Users			Domestic Violence Offenders Compared to Other Violent Offender			Illicit Drug Using-Domestic Violence Offenders		
	B	Odds Ratio	Sig.	B	Odds Ratio	Sig.	B	Odds Ratio	Sig.
Standard or Specialized Supervision	.40	1.4		2.4	10.4	***	-.49	.61	
Urinalysis	1.5	4.5	***	-.30	.74		.18	1.2	
Drug Treatment	1.2	3.2	***	.00	1.0		.07	1.1	
Domestic Violence Treatment	-.79	.45		2.8	17.1	***	.32	1.4	
Mental Health Treatment	-.27	.76		-.57	.57		.96	2.6	*
Any Treatment	.76	2.1	***	1.5	4.4	***	-.28	.76	
Community Service	.38	1.5	*	-.27	.76		-.61	.56	*
Restitution	-.04	.96		-.68	.51	**	.81	2.2	*
Fines	-.23	.79		.00	1.0		.46	1.6	*
Supervision Fees	.17	1.2		.19	1.2		.03	1.0	
Court Costs	.33	1.4		.040	1.0		.29	1.3	

*** p<.001, ** p<.01, * p<.05

As shown in column three, there also was a significant interaction between illicit drug use and type of violent offender on several of the court-imposed probation conditions. Drug-using domestic violence offenders were less likely to have community service orders than the other three groups. The court also was more likely to impose certain probation conditions and sentences on illicit drug-using domestic violence offenders compared to the other three groups. Drug-using domestic violence offenders were 2.2 times more likely to have restitution ordered, 1.6 times more likely to be ordered to pay fines and 2.6 times more likely to have mental health treatment ordered than all other offenders. Judges imposed more conditions on illicit drug-using domestic violence offenders than on any other subgroup, suggesting that the court may be aware of the dangers that this group poses. The threat to public safety of the illicit drug-using domestic violence offenders may explain in part the court's reluctance to impose community service on this group.

As shown in column two, domestic violence offenders compared to other violent offenders were more likely to be placed on specialized probation and to be ordered into domestic violence treatment. Domestic violence offenders were 4.4 times more likely to have some kind of treatment court-mandated compared to other violent offenders. There were no differences in orders to pay supervision fees or court costs.

Probation outcomes

Table 2.5 presents the results of the logistic analyses on probation outcomes. The key differences in probation outcomes were found in the comparison of illicit drug users to non-drug users. Of the 17 measures of probation outcomes, illicit drugs users were significantly different from non-drug users on 14 of these outcomes. Illicit drug users compared to non-drug users were twice as likely to have an unsatisfactory probation discharge rating, 1.7 times more likely to have an administrative discharge and 3.1 times more likely to have their probation revoked. Probation performance of illicit drug users based on other indicators (administrative sanctions, new arrests, technical violations) was also less than stellar compared to non-drug users. Illicit drug users were more likely to receive technical violations for missed appointments, non-payment of financial conditions (fees, fines, court costs), noncompliance with treatment orders and, not surprisingly, for drug use.

Illicit drug users compared to non-drug users were more likely to have at least one arrest while on probation for a non-traffic offense, and were significantly more likely to have an arrest for a violent offense during the first six months after they were discharged from probation. The most frequent new arrests were domestic battery (41) and possession of controlled substance (33). Illicit drug users who were ordered into substance abuse treatment were 2.8 times more likely than non-drug users to be unsuccessful in completing substance abuse treatment, and 5.1 times more likely to unsuccessfully complete domestic violence treatment/sex offender treatment when ordered to participate in that treatment as well. When sex offenders were removed, there was no difference in completion among the groups in domestic violence treatment suggesting that the illicit drug using sex offenders were the unsuccessful group.

As shown in column two of Table 2.5, domestic violence offenders were more likely than other violent offenders to have an unsatisfactory probation discharge rating, to have at least one technical violation for noncompliance with treatment, and to have at least one arrest for a new violent crime while on probation. Over half of the new arrests for violent crimes were domestic violence offenses. I

These findings indicate that illicit drug users and domestic batterers have a much less positive probation performance than other violent offenders and non-drug users. Regarding post discharge performance, the groups did not differ on the number of arrests for any crime after the first six months of being discharged from probation. However, domestic violence offenders compared to other violent offenders and illicit drug users compared to non-drug users were more likely to have a post discharge arrest for a violent offense.

Table 2.5. Comparison of Illicit Drug Users and Domestic Violence Probationers on Probation Outcome

Probation Outcomes	Illicit Drug Users Compared to Non-Drug Users			Domestic Violence Offenders Compared to Other Violent Offenders			Illicit Drug Using-Domestic Violence Offenders		
	B	Odds Ratio	Sig.	B	Odds Ratio	Sig.	B	Odds Ratio	Sig.
Discharge status	.73	2.1	***	.40	1.5	*	-.41	.67	
Revoked or not	1.1	3.1	***	.45	1.5		-.41	.67	
Revoked for new arrest	.73	2.1	***	.33	1.4		-.13	.88	
New arrest(s) while on probation	.95	2.6	***	.29	1.3		-.38	.68	
New non-traffic arrest(s)	.84	2.3	***	.07	1.1		-.08	.93	
New violent arrest(s)	.00	.996		.67	1.9	**	.23	1.3	
Administrative sanction	.55	1.7	*	-.61	.54		.68	1.1	
TV missed appointment	.58	1.8	**	.19	1.2		.06	1.1	
TV nonpayment	.80	2.2	***	.39	1.5		-.44	.65	
TV drug use	2.6	13.9	***	-1.1	.35		1.1	3.0	
TV noncompliance with treatment order	.77	2.2	**	.56	1.6	*	-.52	.59	
Jail days while on probation	.38	1.5		.01	1.0		.59	1.8	*
Did not complete SA treatment	1.0	2.8	***	.45	1.6		-.38	.69	
Did not complete MH treatment	.38	1.5		-.44	.65		.27	1.3	
Did not complete DV or Sex offender treatment	1.6	5.1	*	.50	1.6		-1.2	.31	
Post discharge arrests	.31	1.4		.32	1.4		-.26	.77	
Post discharge arrest for a violent offense	1.0	2.8	*	1.1	2.9	**	-.94	.39	

*** $p<.001$, ** $p<.01$, * $p<.05$

Conclusions

There were significant differences among these four groups of violent probationers on variables in each of the five categories examined. Over all, when significant differences were found, they most often reflected differences between illicit drug users and non-drug users. This was the case for three of the ten demographic variables, seven of the eight criminal history variables, and 14 of the 17 probation outcome measures.   Illicit drug users were more poorly functioning in terms of education, employment and income, had more extensive criminal histories and less positive probation outcomes than non-drug using offenders. Domestic violence offenders differed most sharply from other violent offenders on offense characteristics and were more likely to be ordered into treatment. Significant interaction effects were found for only a few variables, most notable in weapon use and in court ordered conditions. Domestic violence offenders who were also illicit drug users were far more likely to have used a weapon, to have special conditions imposed and to have spent time in jail while on probation than other offenders.

Chapter 3: Which groups of offenders are at high risk of failing to complete domestic batterer treatment?

The dropout rates for court mandated treatment range between 25 to 52 percent (Chalk & King, 1998; Gondolf, 1997), indicating that a significant proportion of domestic batterers do not take advantage of the treatment that is being offered. Some prior studies have found that the extent of treatment participation determines the effectiveness of treatment (e.g., Chen et al., 1989; Taylor, Davis, & Maxwell, 2001). For example, only batterers who attended 75% of the treatment sessions showed a decrease in violent recidivism (Chen et al., 1989). Studies have found that batterers who complete treatment have a significantly lower rate of violent recidivism compared with batterers who fail to complete treatment (For a review of this research see Chalk & King, 1998). These findings highlight that individuals at high risk of dropping out or being prematurely terminated from treatment (i.e., treatment failure) do not benefit from treatment and are at high risk of committing a new violent crime.

Accurate prediction of which offenders are at high risk of treatment failure can lead to better judicial sentencing and improved treatment regimens. For example, under conditions of scarce resources, treatment slots should be given to batterers who are most likely to complete the program. Additionally, in order to create an advantageous treatment environment, it is important to know which offender and offense characteristics predict treatment failure. Batterers who are at high risk of treatment failure may need more structured therapy, additional sanctions for treatment noncompliance, or help with everyday living situations such as employment, educational achievement, welfare assistance, parenting, and stress management.

This study contributes to prior research on predicting treatment attrition in court mandated group treatment for batterers in two ways. First, it examines two possible predictors of treatment failure that have received less attention in this field: (a) family only batterers compared with generalized aggressors (those who are violent to family members, acquaintances, and strangers) and (b) whether offenders also are ordered to undergo substance abuse treatment. Second, it examines which statistical tool is the best method to determine which groups of batterers are at high risk of failing treatment. Researchers make assumptions about how the significant predictors are best combined to increase accuracy when they choose a statistical tool. This paper compares the performance of classification tree analysis and logistic regression.

Literature Review

Which groups of domestic batterers are at high risk of failure? A recent review of the studies predicting which batterers fail at treatment indicates that treatment dropouts are more likely to be unemployed, unmarried, high school dropouts, and to have lower incomes than treatment completers (Daly & Pelowski, 2000). Studies also have consistently found that sex offenders who were never married, those who drop out of high school, or were unemployed had lower rates of successful completion of relapse prevention group therapy for sex offenders (Abel et al., 1988; Craissati & Beech, 2001; Geer et al., 2001; Miner & Dwyer, 1995; Moore, Bergman, and Knox, 1999; Stalans, Seng & Yarnold, 2001; Stalans et al., 2001). It makes intuitive sense that educational achievement predicts success or failure in treatment. Domestic batterer group treatment requires clients to be able to reflect back on their behavior, to assess the circumstances surrounding their behavior, and to arrive at conclusions. Offenders without a high school education also often have inadequate communication skills, and may have difficulty expressing their thoughts and feelings in therapy. One study has found that offenders who have low verbal aptitude are most likely to dropout of unstructured programs (Rooney & Hanson, 2001). Batterers who have never been married may have less motivation to complete treatment than married or divorced batterers who either want to maintain relationships with their partner or their children. Unemployed batterers may have difficulty paying for treatment, and may be less motivated to complete treatment because they do not have the possibility of losing their source of income.

Some studies on profiles of domestic batterers have suggested that generalized aggressors, those who are violent toward family members, acquaintances, and strangers, require a different treatment than family only batterers (Saunders, 1993; Holtzworth-Munroe, & Stuart, 1994). Generalized aggressors compared to family only batterers commit the most frequent and serious violence, have a longer criminal history and are more likely to have substance abuse problems and an antisocial personality (Saunders, 1993; Holtzworth-Munroe & Stuart, 1994). Because generalized aggressors are more tenacious batterers, they may be more likely to drop out of treatment than may family only batterers (Sanders, 1993); only one study has examined this relationship. Rondeau and colleagues (2001) found that domestic batterers who had a criminal record were more likely to abandon treatment if they also had been arrested for assaulting someone other than their intimate adult partner.

Research has found that batterers with a greater number of prior arrests for violent crime were more likely to dropout of treatment (Hamberger, Lohr, & Gottlieb, 2000), which suggests that generalized aggressors, who also have longer violent records, may be more likely to be treatment failures. In addition, some researchers have found that treatment may be less effective for domestic batterers with a long history of criminal offending (Daly & Pelowski, 2000; Fagan et al., 1984; Hamberger and Hastings, 1989). One study has found that batterers who inflicted more severe abuse were more likely to dropout of treatment (Rooney & Hanson, 2001).

Untreated substance abusing batterers also are more likely to drop out of batterer treatment programs (Daly & Pelowski, 2000; Rooney & Hanson, 2001). Although substance abuse may not cause the occurrence of domestic violence, left untreated substance abuse may impair batterers' ability to understand and participate fully in the batterer treatment programs (see Tolman & Bennett, 1990; Bennett, 1995). Prior research has not examined whether domestic batterers are more likely to drop out of domestic batterer treatment if they are also court ordered or self-referred to substance abuse treatment. Treatment providers have documented that domestic batterers attending substance abuse treatment may be more likely to distort the messages of substance abuse treatment to justify further their abusive behaviors (Fazzone, Holton, & Reed, 1997). Domestic batterers may use substance abuse as an excuse of why they committed the violence and may believe that if they stop using illicit drugs or abusing alcohol they will stop the violence (Fazzone, Holton, & Reed, 1997).

Statistical Tools Used to Predict Treatment Failure

Most prior studies have utilized OLS or logistic regression to predict treatment failure. Logistic and survival regression implicitly assumed that significant predictors could be combined in some linear (addition) method, except when interaction terms are entered into the model. Researchers, examining recidivism, have noted that these analyses do not provide information about how to best combine the significant predictors, may provide suboptimal models, and are rarely validated (Hanson & Bussierre, 1998). Steadman et al., (2000) used classification tree analysis (CTA) to assess the predictors of violent recidivism among mentally ill patients recently released from psychiatric hospitals. CTA allows variables to combine in a non-linear fashion and does not assume that all significant predictors are applicable at predicting the risk of all offenders. Researchers have noted that CTA is a better representation of how clinicians typically make risk judgments (Steadman et al., 2000) and may improve the accuracy of predicting domestic batterers' risk of violent recidivism (Kropp and Hart, 2000). Recent studies indicate that CTA compared to logistic regression has higher accuracy in classifying offender populations into low and high-risk groups on recidivism (Silver, Smith, & Banks, 2000; Steadman et al., 2000).

Based on prior studies, we hypothesize that unemployed, never married, and high school dropouts will have higher rates of treatment failure. We also hypothesized that generalized aggressors will be more likely to dropout of treatment compared with family only aggressors, based on clinical profile studies (e.g., Saunders, 1993) and one prior study (Rondeau et al., 2001). Because substance abusing domestic batterers often distort information obtained in substance abuse treatment, we expected domestic batterers in substance abuse treatment to have higher rates of treatment failure than domestic batterers who were not in substance abuse treatment. This study also determines whether CTA, which combines predictors in a non-linear manner, will provide more accurate prediction of treatment failure than logistic regression.

METHOD

Sampling

Staff at the Illinois Criminal Justice Information Authority and Administrative Office of the Illinois Courts (AOIC) created the sampling frame and instrument. The sample consisted of every probationer discharged during the four weeks from October 30 through November 30, 2000. Seasonality appears not to influence probation sentences or probation discharges, suggesting that this time frame did not distort the representation of the sample (see Adams, Olson, & Adkins, 2002). Probation officers who supervised these cases were asked to complete a survey that assessed the offenders' demographics, offense characteristics, prior criminal history, and compliance with probation conditions. Probation officers were asked to refer back to their case file to answer the questions, and to return the forms to AOIC by December 15, 2000. ICJIA staff entered and cleaned the data, which were comprised of 3,364 adult probationers. The probationer information was matched with their Illinois Criminal History Record Information (CHRI) or "rap sheets" which trained research assistant coded to obtain prior criminal history and recidivism while on probation. Throughout Illinois there is a protocol for domestic batterer treatment that requires group treatment where the offender works toward accountability, victim empathy, and understanding the cognitive distortions and justifications used to be violent. The protocol is cognitive behavioral with a feminist influence including components to address attitudes toward women and inappropriate use of power in a relationship. Throughout Illinois, 78 programs comply with the protocol.

Sample Description

All of our analyses focus on the subset of probationers who were in domestic violence treatment. Domestic batterers were defined as those offenders who had prior domestic violence offenses on their criminal history rap sheet and/or were placed on probation for a domestic violence offense. Of the 3,364 adult probationers, 640 were domestic batterers. Of the 640 violent offenders, 333 offenders were domestic batterers who had completed, dropped out, or were unsuccessfully discharged from domestic batterer treatment. The court ordered most of these offenders (94.2%) to participate in treatment, and probation officers referred the other offenders. Of these 333 domestic batterers, 65.3% were involved in specialized domestic violence or sex offender or intensive supervision probation, .6% were monitored in specialized driving while intoxicated or drug probation programs, and 34.1% were on standard probation.

We further divided the sample into two types of domestic batterers: family only aggressors and generalized aggressors. Family only aggressors were identified as either: (1) offenders placed on probation for a domestic violence who had no prior violent crimes on their rap sheet or only prior arrests for domestic violent crimes; or (2) offenders placed on probation for a non-violent crime who had prior arrests for only violent crimes involving domestic violence. Offenders placed on probation for current domestic violence crimes were those arrested for violation of an order of protection or domestic battery, those arrested for a violent crime against an adult intimate former or current partner, and those arrested for criminal damage to property against an adult intimate former or current partner. We included criminal damage to property because domestic batterers frequently commit this offense (Laviolette & Barnett, 2000). Generalized aggressors were identified as those offenders who had been arrested for both domestic violence and other violence based on their prior criminal history and current criminal offense. There were 186 (55.9%) family only aggressors and 147 (44.1%) generalized aggressors who were in domestic violence treatment. This predictor was dummy coded where 0 equals family only aggressors and 1 equals generalized aggressors. Most offenders (95%) were placed on probation for a domestic violence offense.

Predictors of Treatment Failure

From the Rap Sheets, we assessed eight criminal history variables. Each measure represented the number of incidents for that category. The categories included total number of prior arrests, prior probation sentences, prior convictions, and number of prior arrests for five specific crime categories (violent, domestic violence, drugs, property, and driving while intoxicated). The sample had an average of 5.52 total prior arrests (median = 3), and averaged 2.2 prior arrests (median = 1) for violent crimes. Most of the sample had at least one prior arrest for some crime (85.9%) and 71.3% had a prior arrest for a violent offense. A significant proportion had at least one prior arrest for a domestic violent offense (42.6%), drug offense (28.7%), and a small percent for a driving while intoxicated offense (6.0%). A little over half (51.5%) had at least one prior conviction and 41.6% had previously served a probation term. This sample thus is well experienced with the criminal justice system and has a track record of committing violent offenses as well as other offenses.

From the code form completed by probation officers, we assessed the offenders' demographic characteristics, the characteristics of the offense, the conditions of probation, and the offender's compliance with conditions. Eight demographic measures were assessed at the time of intake: age (mean = 33.1; sd = 9.00), annual income, education, race, gender, marital status, living status, and number of children living with probationer. Except for age, all demographic measures were treated as categorical variables. Most probationers were male (92%) who were living with family or friends (77.5%) but were not living with children (63.1%). Offenders who were never married comprised the largest proportion of offenders (45.3%), and 30.2% were currently married. Caucasian offenders comprised 40.6% of the sample, 37.4% were African-Americans and 20.5% were Hispanic Americans. Two-thirds of the offenders (67.5%) were employed full-time or part-time, although 42.9% had no high school diploma and 55.3% of the sample lived in poverty earning less than $15,000 annually. Only 10.9% had some college, and 19% of the offenders had an annual income of $25,000 or more.

We used three characteristics of the offense as potential predictors: whether a weapon was used or not, offender's relationship to the victim and victim's gender. In one third of the cases a weapon was used. In the current offense, most victims were women (86.6%), and were an intimate adult partner (87.4%).

Two dichotomous measures (0 = no; 1 = yes) assessed whether offenders had a current alcohol abuse problem, and whether they were in substance abuse treatment. A substantial percentage of offenders (58.2%) abused alcohol and 33.9% were court-ordered for substance abuse treatment (2 offenders enrolled in substance abuse treatment on their own choice). In addition, we assessed an offender's use of illicit drugs using a categorical variable with four categories; over half of the offenders (66.4%) did not admit to using any illicit drugs, 17.6% used only marijuana, 4.5% used only hard illicit drugs other than marijuana, and 11.5% used both marijuana and other illicit drugs. Only a small percentage (4.8%) had a violation of probation petition filed for failure to comply with abstaining from the use of illicit drugs or alcohol.

Two dichotomous measures assessed whether offenders had prior psychiatric treatment and were currently in mental health treatment. Only a small percentage of offenders (6.3%) were currently in mental health treatment, and 15.8% had prior psychiatric treatment. In addition, we assessed the number of different kinds of treatments (e.g., mental health, domestic violence, and substance abuse) in which offenders were participating. About two-thirds (63.1%) were involved only in domestic violence treatment, one-third (32.4%) were involved in two kinds of treatment, and 4.5% were involved in three or more different treatments.

Results and Discussion

The result and discussion portion has three major sections. First, we examine the bi-variate significant predictors of treatment failure. Second, we conduct a CTA to determine the groups at high risk of treatment failure while on probation. Lastly, we compare the performance of the CTA with the performance of logistic regression at predicting treatment failure.

To determine the significant predictors at the bi-variate level, we employed univariable optimal discriminant analysis (UniODA), which provides the maximum possible accuracy in classifying cases; it has been used in other studies that predicted violent recidivism among domestic batterers (Bennett, Goodman, & Dutton, 2000). In order to determine the relative performance of each significant predictor, we used the percentage of total possible improvement in classification accuracy achieved with the predictor—above the classification accuracy achieved through chance alone. This measure is a standardized test statistic called the "effect strength for sensitivity" (ESS).[vi] ESS can range between 0 and 100, where 0 means no improvement in classification accuracy above chance, and 100 means that the predictor explains all variation (errorless classification). For a two-category variable, chance could achieve a mean sensitivity across classes of 50%, and thus this corresponds to an ESS of 0. A mean sensitivity (referring to the average of the percentage correctly classified for completers and the percentage correctly classified for treatment failures) of 75% across classes lies halfway between chance and perfect performance and corresponds to an ESS of 50% (Yarnold, Soltysik, and Bennett, 1997). Predictors can be ranked as weak, moderate, or strong, based on the ESS. The accuracy in classification above chance performance is considered weak when ESS is less than 25%, moderate when ESS is between 25% and 49%, and strong when ESS is 50% or higher.

Prior research has noted the importance of determining whether significant predictors will generalize to other samples and to the population or whether the significance is due to outliers or other data abnormalities. For each predictor, we conducted a jackknife validity analysis called a leave-one-out (LOO) analysis where classification for each observation is based on all data except the case being classified. The LOO analysis is particularly effective at detecting the undue influence of outliers or variations in the cut off score on a continuous variable. Predictors are generalizable if they have the same accuracy at classifying cases (measured by the ESS) in the validity analysis as in the original sample.   Thus, significant predictors that will not replicate in a new data set have different ESS's in the original sample and the validity analysis. We report whether a predictor was generalizable or ungeneralizable.

Univariate Predictors of Treatment Failure

Overall, 31.8% of the domestic batterers (N = 105) refused to attend treatment or were prematurely terminated from treatment; of this group, 75% did not attend and treatment providers terminated the other 25% for noncompliance. Based on univariate analyses for the entire sample of domestic batterers, Table 1 presents all of the significant and generalizable predictors of treatment failure while on probation. In column one of Table 1, the value of the variable that is related to a higher risk of treatment failure is described, and the probability level and ESS are presented in column two and three respectively. We highlight only the most important findings in the text, and the reader is referred to Table 3.1 for a complete description of all generalizable predictors.

Only criminal history measures that were specific to domestic violence were significant and generalizable predictors of treatment failure. Generalized aggressors and batterers with two or more prior arrests for domestic violence were at a higher risk of treatment failure. Supporting previous research (for a review see Daly & Pelowski, 2000), three demographic measures, unemployed, never married, and high school drop-out, were the strongest predictors of treatment failure. Unemployment was the strongest risk predictor and explained 35.1% of the variation in classification accuracy above chance performance.

Table 3.1 also shows that several measures of alcohol or illicit drug abuse were significantly related to treatment failure. Consistent with prior research (e.g., Rooney & Hanson, 2001), batterers who have alcohol or drug problem are at a higher risk to drop out of treatment or be prematurely terminated from treatment. Treatment providers also have speculated that batterers who have both a battering problem and a substance abuse problem are more difficult to

Table 3.1. Significant and Generalizable Predictors of Unsatisfactory Completion of Treatment for Domestic Batterers

Significant Predictors	p-value	ESS
Demographic Characteristics		
Unemployed or retired	.0001	35.09%
Did not complete high school	.0001	27.84%
Never Married	.0001	26.24%
Problems with drugs or alcohol		
Prior arrest for a drug offense	.0001	27.12%
Problem with alcohol	.005	20.01%
In substance abuse treatment	.001	19.11%
Violated for using drugs or alcohol	.003	8.25%
Prior criminal history		
Two or more prior arrests for domestic violence	.029	14.90%
Past arrest for violence against acquaintances/strangers	.022	17.23%
Generalized aggressor	.025	13.33%
Offense Characteristics		
Used a weapon	.024	14.49%
Probation Conditions		
On specialized or intensive probation	.023	13.76%

treat (Fazzone, Holton, & Reed, 1997). These findings support this observation and indicate that batterers with substance abuse problems may need a different or more coordinated treatment approach. The field has begun to recognize the need to coordinate substance abuse and domestic violence treatment for substance abusing batterers (see Fazzone, Holton, & Reed, 1997).

CTA Analyses Predicting Treatment Failure

Finding characteristics that predict treatment failure for the entire sample is an important first step, but in order to identify high-risk groups researchers must determine how to combine these significant predictors. We employed CTA, via optimal discriminant analysis (Yarnold, 1996), to identify the groups that were at high-risk of treatment failure.[vii] For each CTA analysis, the variable with the strongest ESS is entered at each step. Variables that were not generalizable were excluded from entering the CTA model at that step. We conducted six CTA analyses, starting the models with the predictors: generalized aggressor, employment, marital status, education level, prior arrest for drug crimes, and substance abuse treatment. Four of the six models identified the same high risk group: offenders with a substance abuse problem that were either unemployed or high school dropouts. This group of offenders had between a 60 to 68% chance of dropping out of treatment.

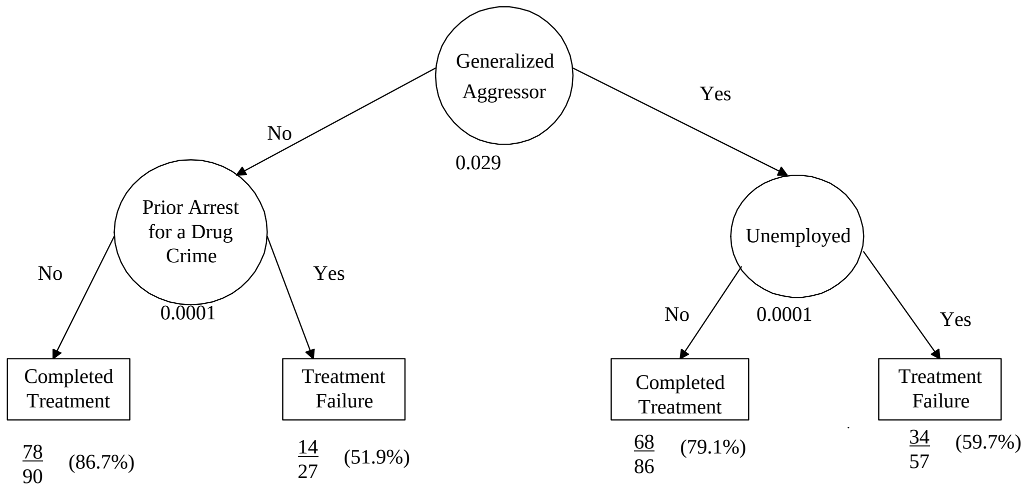
The model with the highest predictive power began with generalized aggressor or not and showed moderate performance (ESS = 41.7%). It accurately classified 61.5% of the treatment failures and 80.2% of the completers. It had an overall classification accuracy of 74.6%. Figure 1 presents this three variable model.

A brief explanation of Figure 1 representing the CTA model predicting treatment failure will assist the reader in understanding the figure. The circles in the model identify the significant predictors, and the probability level that corresponds to that predictor is underneath the circle.

By following the arrows to the rectangular boxes, the defining characteristics of a cluster are obtained. The rectangular box indicates the outcome predicted for this cluster by the model: in the present case, whether completed treatment or treatment failure. Beneath the rectangular box is a ratio. The number in the numerator indicates the number of correctly classified offenders for this outcome and the number in the denominator indicates the total number of offenders in the cluster. The number in parentheses is the accuracy in classification; when the outcome is "completed treatment" it is necessary to subtract the accuracy in classification from 100 to obtain the likelihood that offenders in this cluster would fail at treatment.

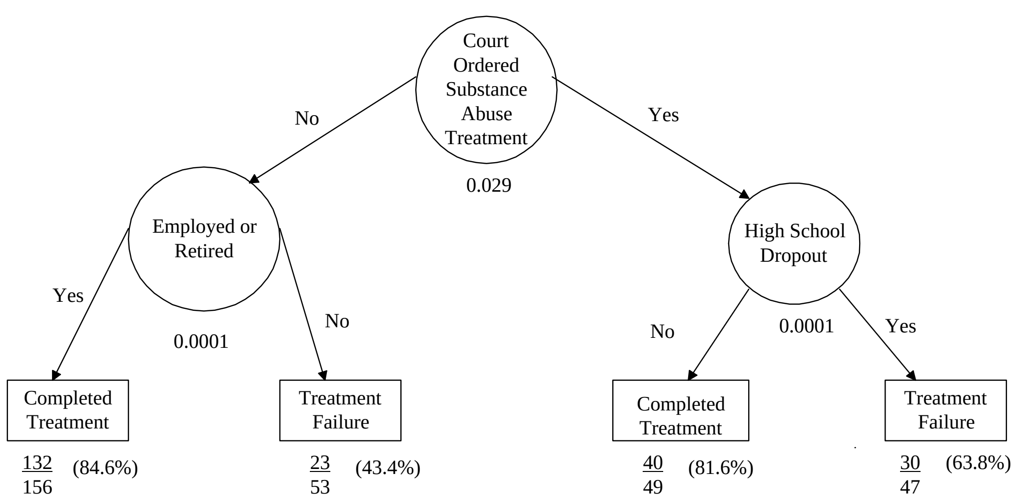
Based on Figure 1, employed generalized aggressors have a 19.9% chance of treatment failure whereas unemployed generalized aggressors have a 59.7% chance. Family only batterers who do not have any prior arrests for drug crimes have a high chance of successfully completing treatment and have a very low chance of treatment failure (13.6%). Family only batterers with at least one prior arrest for a drug crime have a higher chance of treatment failure. Additional research using characteristics of treatment as well as probation may improve the accuracy of predicting treatment failure for family only batterers.

Figure 1. CTA Model Predicting Treatment Failure



The CTA model beginning with whether the batterer was ordered to attend substance abuse treatment was the second strongest model and showed moderate performance (ESS = 37.2%); this model is presented in Figure 2.[viii]

Figure 2. CTA Model Predicting Treatment Failure



Offenders who were not ordered into substance abuse treatment and were employed or retired had a high chance of successful completion of treatment, with only 15.4% either dropping out or being unsuccessful discharged from treatment. Unemployed batterers who were not ordered to attend substance abuse treatment had a moderate chance of successfully completing domestic batterer treatment, with 43.4% failing at attending or complying with treatment.

For offenders who were ordered to attend substance abuse treatment, 63.8% of the high school dropouts did not comply with treatment whereas only 19.4% of offenders with a high school education did not comply with treatment. This finding suggests that offenders who dropped out of high school may be more likely to distort the messages of substance abuse treatment, may need more coordination between substance abuse and domestic violence treatment, or may be less motivated to attend domestic violence treatment compared to substance abuse treatment.

If high school dropouts are less motivated to attend domestic violence treatment than substance abuse treatment, there should be a large percentage that completed substance abuse treatment but were treatment failures at domestic batterer treatment. This hypothesis can be tested. We conducted a chi-square analysis crossing completion of substance abuse treatment with completion of domestic violence treatment while controlling for education level. High school dropouts are less motivated to attend both types of treatment than are offenders with a high school degree. For both high school dropouts and those with a high school degree, offenders who failed at one treatment were more likely to fail at the other treatment, (X^2 (1) = 10.76, $p < .001$ and X^2 (1) = 32.1, $p < .0001$). Little support was shown for differential motivation. Among high school dropouts, 12% completed domestic violence treatment but failed at substance abuse treatment and 9.1% completed substance abuse treatment but failed at domestic violence treatment. Almost twice as many offenders with a high school education (62.5%) compared with high school dropouts (33%) completed both substance abuse treatment and domestic violence treatment. Almost twice as many high school dropouts (45.5%) compared with offenders who completed high school (26.8%) failed to attend or were unsuccessfully discharged from both substance abuse and domestic violence treatment.

Comparison of CTA and Logistic Regression

Does the CTA approach achieve better classification accuracy of treatment failures than logistic regression? To address this question, we first conducted a stepwise logistic regression and used as predictors only those variables that appear in Table 1 to insure that only generalizable predictors entered the model. We then conducted a forced entry logistic regression of all predictors that were significant in the step-wise analysis to reduce the number of missing cases. Table 3.2 presents the final logistic model.

Table 3.2. Results of the Logistic Regression Predicting Treatment Failure

Significant Predictors	b	p-value	Odds Ratio
Weapon	.87	.008	2.4
Did not complete high school	.33	.40	1.4
Unemployed at intake interview	1.4	.0001	4.0
Court ordered substance abuse treatment	-.41	.44	.66
Interaction term: High school dropouts ordered to Attend substance abuse treatment	1.9	.006	6.8
Constant	-2.3	.0001	
Overall Model Statistics	Statistic value	p-value	
Model Chi-Square (5)	59.2	.0001	

The final logistic model used six predictors and classified 275 batterers, with employment and educational level the strongest predictors. Offenders who were in substance abuse treatment were 1.87 times more likely to fail treatment than were offenders who were not in substance abuse treatment. There was a trend indicating that generalized aggressors compared to family only batterers were 1.7 times more likely to fail treatment. We also tested two interaction terms: (1) unemployed generalized aggressor; and (2) high school dropouts ordered to attend substance abuse treatment. The interaction between unemployed and generalized aggressor was not significant. As shown in Table 2, the interaction between high school dropouts and those ordered to attend substance abuse treatment was significant.

Table 3.3 presents a comparison of logistic regression and CTA on measures of performance. Both CTA models compared to logistic regression show stronger performance, and are more parsimonious using three or four variables compared to six variables in the logistic model. Based on the ESS, the CTA model starting with generalized aggressors shows a 37% gain above what logistic regression achieved in the possible improvement in classification accuracy beyond chance performance. The CTA model starting with whether ordered to have substance abuse treatment shows a 15% gain above what logistic regression achieved in the possible improvement in classification accuracy beyond chance performance.

Table 3.3 Performance of Logistic Regression and CTA on Predicting Treatment Failure

Performance Indicators	Logistic Regression	CTA starting with generalized aggressor	CTA starting with substance abuse treatment
Effect Strength of Sensitivity	29.0%	41.7%	36.5%
Classification Accuracy at Predicting Treatment Failure (sensitivity)	36.6%	61.5%	55.4%
Classification Accuracy at Predicting Satisfactory Progress (specificity)	92.4%	80.2%	81.1%
Overall Classification Accuracy	77.6%	74.6%	73.5%
Number of Predictors	5	4	3

Both CTA models compared to logistic regression also almost double the accuracy of classifying treatment failures, which is the critical outcome. Given that 69% of the sample actually had successful completion, the CTA models do better than what chance could achieve in a maximum likelihood approach in predicting successful completion. By contrast, the logistic regression model accurately predicts 92.4% of the cases that had successful completion, but only accurately predicts 37% of the treatment failures. Logistic regression has a slightly higher overall classification accuracy than both CTA models; overall classification accuracy, however, is not an informative performance indicator because it often distorts how well a model did at predicting the critical outcome value. If the objective is to predict which cases are at high risk of treatment failure, it is clear that the CTA approach outperforms logistic regression and should be used in future research on this topic.

Conclusions

This study adds to the growing literature on predicting treatment failure by identifying groups of domestic batterers that are at high risk of treatment failure. The findings highlight the importance of separating generalized aggressors from family only batterers in predicting treatment failure. The findings also underscore the importance of examining whether domestic batterers are ordered to obtain substance abuse treatment. Many studies predicting treatment attrition in domestic batterer treatment have used samples that do not contain individuals with severe substance abuse problems (e.g., Rooney & Hanson, 2001; Rondeau et al., 2001), and have not addressed whether court-order substance abuse treatment increases the risk of failing to complete domestic batterer treatment. Our study indicates that high school dropouts that are ordered to undergo substance abuse treatment are at a very high chance of being prematurely terminated or refusing to attend domestic violence treatment as well as substance abuse treatment.

Supporting prior research (e.g., Daly & Pelowski, 2000), three demographic variables were the strongest predictors in univariate analyses: never married batterers, unemployed batterers, and high school dropouts had a significantly higher risk of treatment failure. The CTA analyses revealed three groups that were at high risk (at least a 60% chance) of treatment failure: (a) unemployed generalized aggressors; (b) high school dropouts ordered into substance abuse treatment; and (c) unemployed offenders with a substance abuse problem. These groups illustrate that offenders that have problems with basic life skills and either a substance abuse problem or violent tendencies toward all people are less likely to benefit from domestic batterer treatment.

The CTA model also revealed that family only batterers with one prior arrest or no prior arrests had a very high chance of progressing in treatment. Similarly, offenders who were not ordered into substance abuse treatment and did not have any prior arrests for drug crimes had a very low chance of treatment failure.

CTA compared to logistic regression is a better statistical approach to determine which groups of offenders are at high risk of treatment failure. The performance of logistic regression at accurately predicting treatment failure was substantially suboptimal compared to the CTA approach. Moreover, the CTA model was validated using a leave-one-out validity analysis whereas the logistic regression model was not validated using the maximum likelihood algorithm, which means that we gave logistic regression an opportunity to present the best possible model. Despite this advantage, logistic regression did not perform as well as CTA on the critical performance indicators. This finding indicates that future research should pursue the

CTA approach to replicate these findings and determine additional groups at high risk of treatment failure. As research on high risk groups accumulates, risk assessment tools for determining the risk of treatment failure may be developed, and may be useful for treatment providers when a limited number of treatment slots are available.

High school dropouts who are abusing alcohol or illicit drugs have a high risk of failing to attend or being unsuccessfully discharged from both substance abuse treatment and domestic batterer treatment. In addition to coordinating substance abuse and domestic violence treatment, treatment providers may need to tailor their treatment for substance-abusing high school dropouts. What are some components of these treatments that are not beneficial to substance abusing high school dropouts? Both therapies are often group therapy where clients must have good communication skills and where discussion amongst the clients is crucial. Prior research, in which 76% of the sample was self-referred, has found that batterers with low verbal aptitude have a high dropout rate from unstructured domestic batterer treatment, but a significantly lower dropout rate from structured domestic batterer treatment (Rooney & Hanson, 2001). A large percentage of individuals who have not completed high school have difficulty expressing themselves during group discussions and may have lower ability to understand communication from others, and with this little verbal aptitude may feel frustrated in unstructured group therapy. Substance-abusing high school drops also may need to learn coping skills to handle their depression, anger, and other negative emotions before they are ready to address taking responsibility for their violence and substance abuse. Individual counseling to address their emotions in conjunction with assistance for obtaining or improving job skills may be helpful. Treatment providers also have suggested that domestic batterers may need to make progress in controlling their substance abuse before they are ready to benefit from domestic batterers treatment (Fazzone, Holton, & Reed, 1997). Future research can examine treatment components that may contribute to the high treatment failure rate for substance-abusing high school dropouts, and can examine whether this group of batterers also is most likely to distort the principles and messages of substance abuse treatment such as alcoholic anonymous.

Future research can investigate whether characteristics of the treatment, such as structured groups, enhanced life skills, and sanctions for noncompliance, lower the risk of treatment failure for these high-risk groups. The criminal justice may use information about groups at high-risk of treatment failure to make decisions that reserves treatment for those who have a better chance of benefiting from the treatment that is offered. As research progresses in this area, treatment providers may accumulate enough information to tailor treatments for high-risk groups of offenders.

Chapter 4: Identifying Three Types of Violent Offenders and Predicting Their Recidivism and Performance While On Probation: A Classification Tree Analysis

Offenders who are convicted of violent crimes are often sentenced to probation (Greenfeld, 1996). Probation officers assess the risk that offenders will commit a new violent crime or any crime while on probation to determine the extent of supervision and the conditions of probation. Probation departments generally categorize offenders as low, medium, and high risk, with each level of risk corresponding to a more intensive monitoring strategy. For example, violent offenders assessed as high risk may be placed on specialized or intensive supervision probation. The specialized probation may require probationers to have two office contacts with their probation officer per month, to allow the officer to visit and search their home once a month at an unannounced time, to submit to random drug and alcohol testing, to abide by a curfew, to have no contact with the victim, and to participate in treatment. Offenders assessed as medium and low risk may be placed on standard probation and the low risk offenders compared to the medium risk offenders will have fewer face-to-face contacts with their probation officer and fewer probation conditions. Thus, the probation officers' risk assessments are designed to prevent additional violent behavior and assist in more efficient allocation of the resources used to monitor violent offenders.

Research on predicting violent recidivism has primarily focused on mentally disordered offenders (for a review see Bonta, Law & Hanson, 1998; Quinsey, Harris, Rice, & Cormier, 1998), and mentally ill patients in the community (e.g., Lyon, Hart & Webster, 2001; Monahan et al., 2000; Steadman et al., 2000; Swanson, 1994). Fewer studies have examined the predictors of violent recidivism while violent offenders are serving a probation sentence, except those focusing on domestic batterers (e.g., Aldarondo & Sugarman, 1996; Bennett, Goodman, & Dutton, 2000; Kropp & Hart, 2000; Goodman, Dutton, & Bennett, 2000; Shepard, 1992). This literature has led to the creation of risk assessment scales that attempt to provide a more accurate assessment of the risk of violent recidivism. Moreover, the research on predicting violent recidivism has begun to raise controversial issues that may lead to improvements in risk assessment scales.

One unresolved issue is which statistical tool will provide optimal classification accuracy. Actuarial risk assessment scales generally have been based on OLS and logistic regression analyses, with a few exceptions (Monahan et al., 2000; Steadman et al., 2000; Silver, Smith & Banks, 2000). These analyses explicitly assume that significant predictors could be combined in some linear (addition) method, and do not empirically test how best to combine the significant predictors to provide optimal classification accuracy. Furthermore, when interaction terms are entered into logistic models, these interactions represent non-linear effects and are combined with the main effects using a weighted addition method to obtain a risk probability. By contrast, classification tree analysis (CTA) allows variables to combine in a non-linear fashion and does not assume that all significant predictors are applicable at predicting the risk of all offenders. Studies have found that Iterative Classification Tree (ICT) (Monahan et al., 2000; Steadman et al., 2000) and standard CTA (Silver et al., 2000; Silver & Chow-Martin, 2002) compared to logistic regression has higher accuracy in classifying offender populations into low and high-risk groups on violent and general recidivism. However, Iterative Classification Tree and logistic regression, based on ROC analysis, showed similar accuracy at identifying violent recidivists among mentally ill patients (Steadman et al., 2000). Researchers have noted that CTA may be a better representation of how clinicians typically make risk judgments (Steadman et al., 2000) and may improve the accuracy of predicting domestic batterers' risk of violent recidivism (Kropp & Hart, 2000). Studies, comparing CTA and logistic regression, have focused on predicting mentally disordered offenders' violent recidivism or criminal offenders' general recidivism. Thus, the current study builds upon this research and examines whether CTA or logistic regression provides higher accuracy in predicting violent recidivism of a wide range of violent offenders as they serve their probation sentence.

Another important, but unexamined issue is how well dynamic risk factors, those that indicate change in an offender's behavior, predict violent recidivism. Hanson and Harris (2000) found that recidivists compared with non-recidivist sex offenders showed increased anger, were more often disengaged from or uncooperative with treatment and community supervision, missed scheduled appointments, and attempted to deceive probation officers. These dynamic risk factors predicted sexual recidivism even after controlling for static risk factors such as criminal history, offense characteristics, and offender demographics (see also Hanson & Harris, 2001). Building on this research, we address whether treatment noncompliance, noncompliance with attending scheduled office appointments, and noncompliance with abstaining from illicit drugs or alcohol predict violent recidivism.

Two intertwined issues that have not received appropriate attention are whether all violence derives from the same sources and whether characteristics associated with high risk of violent recidivism apply to all groups of violent offenders. General criminological theories typically assumed that all offenders commit crimes based on the same reasons such as lack of self-control and differing opportunity (e.g., Alarid, Burton & Cullen, 2000). Across studies, younger age, never married status, living in poverty, a history of violence, and violence against strangers or acquaintances have been consistent significant predictors of violent recidivism (for reviews see Gendreau, Little, & Goggin, 1996; Hanson & Bussiere, 1998; Hanson & Harris, 2000; Klassen & O'Connor, 1994). Furthermore, researchers have developed the Violent Risk Appraisal Guide (VRAG) to predict violent recidivism in all offender populations and have shown that the VRAG significantly predicts violent recidivism committed by sex offenders, violent offenders released from prison, and domestic batterers released from a maximum security psychiatric facility (e.g., see Rice, 1997; Hilton, Harris, & Rice, 2001). Continuing the pursuit for common predictors, the Psychopathy Checklist: Screening Version (PCL: SV; Hart & Hare, 1997) or the HCR-20 Violence Risk Assessment Scheme (Grann, Belfrage, & Tengstrom, 2000; Douglas & Webster, 1999) also have been used to predict violent recidivism in all offender populations.

Other researchers have developed violent risk assessment tools for special populations such as domestic batterers (for a review see Dutton & Kropp, 2000; Kropp & Hart, 2000). These risk assessment tools implicitly assume that different risk factors predict domestic batterers' violent recidivism. Consistent with the assumptions that subgroups of violent offenders may have different risk markers, Klassen and O'Connor (1994) suggested that future research should consider the possibility that "there are different types of violence, . . . and even hypothesize that some violence patterns are very nonspecific and based on generalized aggression, while others are highly focused, learned patterns of behavior" (p. 246). Prior research, however, has not followed their suggestion and empirically tested whether subgroups of violent offenders have different or similar risk characteristics associated with violent recidivism.

Building upon descriptive clinical studies, the current study empirically tests whether three subgroups of violent offenders have unique characteristics that predict violent recidivism. Prior research has discovered three subgroups of violent offenders: family only aggressors, non-family only aggressors, and generalized aggressors (Holtzworth-Munroe & Stuart, 1994; Saunders, 1992; Saunders, 1993; Olson & Stalans, 2001; Tweed & Dutton, 1998). Family only aggressors direct their violence only against family members whereas non-family only aggressors are violent toward only friends, acquaintances, and strangers (e.g., armed robbery, fighting in bars). The third group is called generalized aggressors because they are violent toward family members, friends, acquaintances, and strangers. Based on prior research, generalized aggressors compared to family only aggressors were of lower social status, were less remorseful, had more conservative attitudes toward women, and had more extensive prior arrests for violent and non-violent crimes (Holtzworth-Munroe & Stuart, 1994; Saunders, 1992; Saunders, 1993). Generalized aggressors committed the most frequent and serious violence, though both family only aggressors and generalized aggressors were likely to have substance abuse problems (Saunders, 1993; Holtzworth-Munroe & Stuart, 1994). Research has produced inconsistent findings on whether domestic batterers have lower rates of violent recidivism compared to other violent offenders (Hilton et al., 2001; Olson & Stalans, 2001). Both of these studies, however, did not separate generalized aggressors from family only aggressors. The current research tests whether generalized aggressors have higher rates of violent recidivism than family only and non-family only aggressors.

Consistent with recent studies (Silver et al., 2000; Steadman et al., 2000), this study employs a cutting edge statistical tool, classification tree analysis (CTA), to assess the optimal combination of significant static and dynamic risk predictors of violent recidivism while offenders are serving their probation sentence. We hypothesized that generalized aggressors will have higher violent recidivism rates compared with family only and non-family only aggressors. We hypothesized that dynamic predictors (e.g., treatment noncompliance) will be critical predictors of violent recidivism for all violent offenders. Generalized aggressors have learned to use violence to get what they want in all situations whereas family only aggressors have more specific motivations when they use violence and are less likely to be reported to the police (Holtzworth-Munroe & Stuart, 1994; Saunders, 1992; Saunders, 1993). Moreover, prior research has found that prior violence is less predictive of violent recidivism among domestic batterers than is the score from the Danger Assessment Scale, which contains unique information targeted at relationships involving domestic violence (Goodman et al., 2000). Based on this information, we hypothesized that the total number of prior arrests for violent crimes will be more predictive of generalized aggressors' violent recidivism than of family only aggressors' violent recidivism.

Methods

Procedure

Staff at the Illinois Criminal Justice Information Authority (ICJIA) and Administrative Office of the Illinois Courts (AOIC) created the sampling frame and instrument. The sample consisted of every probationer discharged during the four weeks from October 30 through November 30, 2000. Seasonality appears not to influence probation sentences or probation discharges, suggesting that this time frame did not distort the representation of the sample (see Adams, Olson, & Adkins, 2002). Probation officers who supervised these cases referred back to their case file and completed a survey that assessed the offenders' demographics, offense characteristics, criminal history, and compliance with probation conditions. ICJIA staff entered and cleaned the data, which were comprised of 3,364 adult probationers. The probationer information was matched with their Illinois Criminal History Record Information (CHRI) or "rap sheet" which trained research assistant coded to obtain criminal history and recidivism while on probation.

Defining violent offenders. All of our analyses focus on the subset of probationers who were violent offenders. Violent offenders were defined as those offenders who had prior violent offenses on their criminal history rap sheet and/or were placed on probation for a violent offense. Of the 3,364 adult probationers, 1,344 were violent offenders. Offenses that qualified as violent crimes included: First and second degree murder, involuntary manslaughter, reckless homicide, armed or unarmed robbery, battery, reckless conduct, domestic battery, assault, aggravated arson, unlawful use of weapon, aggravated discharge of a firearm, harassment, mob action, intimidation, unlawful restraint, violation of an order of protection, and violation of an Illinois Bail Bond.[ix] Attempted crimes for these offenses as well as specific versions of these offenses such as aggravation (e.g., aggravated battery) or those against a police officer or child were also included.[x] The most frequent crimes were domestic battery (N = 311) and some form of battery (including aggravation, N = 190), with 52.1% of the violent probationers placed on probation for a misdemeanor crime and the remainder placed on probation for a felony including six offenders serving probation for some form of homicide. Because many domestic violence cases are dropped before conviction, the cases that are sentenced to probation for this crime may reflect the more serious and repeat domestic batterers. Only 54.8% of the 1344 violent probationers were on probation for a current violent offense and the remainder was convicted of nonviolent offenses with the most frequent offenses including theft (N = 46), burglary (N = 36), unlawful possession of a controlled substance (N = 98) and driving while intoxicated (N = 139).

Predictors

Defining subsets of violent offenders. We further divided the sample into three types of violent offenders: family only aggressors, non-family only aggressors, and generalized aggressors. Family only aggressors were identified as either: (1) offenders placed on probation for domestic violence who had no prior arrests or only prior arrests for domestic violent crimes; or (2) offenders placed on probation for a non-violent crime who had prior arrests for only violent crimes involving domestic violence. Domestic violence was defined as a violation of an order of protection, domestic battery, and those arrested for a violent crime or criminal damage to property against an adult intimate former or current partner. We included criminal damage to property because domestic batterers frequently commit this offense (Laviolette & Barnett, 2000). Non-family only aggressors were identified as either: (1) offenders who were placed on probation for a violent crime against an acquaintance or stranger and had no prior violent crimes or only crimes that did not involve domestic violence; or (2) offenders placed on probation for a non-violent crime who had prior arrests for only violent crimes that did not involve domestic violence. Generalized aggressors were identified as those offenders who had been arrested for both domestic violence and other violence based on their criminal history and current criminal offense. There were 321 (24%) family only aggressors, 717 (53.5%) non-family only aggressors, and 302 (22.5%) generalized aggressors.

Overall, generalized aggressors had a higher mean number of total prior arrests (M = 8.2) compared to non-family only aggressors (M = 5.6) and family only aggressors (M = 2.3), $\underline{F}\,(2, 1159) = 52.4$, $\underline{p} < .001$. All means are different using Bonferonni post-hoc comparison test. The majority of generalized aggressors (82%) had two or more prior arrests for violent crimes whereas only 36% of the non-family only aggressors and 14% of the family only aggressors had two or more prior arrests for violent crimes, X^2 (4) = 362.07, $\underline{p} < .0001$. Based on these findings, it is clear that this sample of generalized aggressors were more tenacious repeat violent offenders than either family only or non-family only aggressors. These findings support prior studies (e.g., Saunders, 1992) and provide concurrent validity for our measure of the three types of offenders.

Type of prior violence in criminal history. We also created a variable that captured the type of violence in their criminal history: 17% had no prior arrests for violent crimes, 55% were non-family only violent crimes, 11% had family only violent crimes, and 16% had both crimes against family members and non-family members.

Frequency of prior arrests. From the rap sheets, we assessed eight criminal history variables. Each measure represented the number of incidents for that category. The categories included total number of arrests, probation sentences, convictions, and number of arrests for five specific crime categories (violent, domestic violence, drugs, property, and driving while intoxicated). The sample had an average of 5.74 total arrests (median = 4), and averaged 1.95 arrests for violent crimes. Most of the sample had at least one prior arrest for some crime (92%) and 83% had a prior arrest for a violent offense. A significant proportion had at least one arrest for a property crime (47%), domestic violence (27%), drug offense (34%), and driving while intoxicated offense (10%). A little over half (57%) had at least one prior conviction and 47% had served a prior probation term. This sample thus is well experienced with the criminal justice system and has a track record of committing a wide range of offenses. In addition, 6.8% (N = 91) of the violent offenders are gang members.

Demographics. There were eight demographic measures taken at the time of intake: age (mean = 31.9; sd = 10.54), annual income, education, race, gender, marital status, whether living alone or with family or friends, and number of children living with probationer. Except for age, all demographic measures were treated as categorical variables. Most probationers were men (87%) who were living with family or friends (83%) but were not living with children (67%). Over half were never married (56%), and 24% were currently married. Caucasian offenders comprised 45% of the sample, 39% were African-Americans and 14% were Hispanic Americans. Most offenders (60%) were employed full-time or part-time, although 48% had no high school diploma, 39% had a high school diploma and 13% had some college. Most offenders (60%) lived in poverty earning less than $15,000 annually, with only 9% having an annual income between $25,000 and $34,999 and 7% having an annual income of $35,000 or more.

Offense Characteristics. Five offense characteristics served as predictors: whether a weapon was used or not, whether placed on probation for a violent offense, whether placed on probation for a domestic violent offense, offender's relationship to the victim and victim's gender. In one quarter of the cases a weapon was used. A little over half of the offenders (56%) were placed on probation for some kind of violent offense and 32% were placed on probation for a domestic violent offense. Two-thirds of the victims were female. Because many of the offenders were placed on probation for a non-violent crime, the relationship to the offender was unclear in half of the cases, while in 30% the victim was a family member, and in 19% the victim was a stranger or acquaintance.

Substance use. A dichotomous measure (0 = no; 1 = yes) assessed whether offenders had a current alcohol abuse problem, with 62% abusing alcohol. In addition, we assessed an offender's use of illicit drugs using a categorical variable with four categories; over half of the offenders (57%) did not admit to using any illicit drugs, 20% used only marijuana, 7% used only hard illicit drugs other than marijuana, and 16% used both marijuana and other illicit drugs.

Mental health. Dichotomous measures assessed whether offenders were participating in specific treatments. Only a small percentage of offenders (10%) were currently in mental health treatment, 28% were in domestic violence treatment, 40% were in substance abuse treatment, and 16% had prior psychiatric treatment. In addition, a little over one-third (36%) were involved in no treatment, 47% had one kind of treatment, and 15% were involved in two or more kinds of treatment.

Probation Conditions. The conditions of probation may also influence whether offenders commit new crimes while on probation. Probation conditions may increase monitoring and guidance and may deter offenders from committing new crimes. Three dichotomous measures (0 = no; 1 = yes) assessed whether the judge ordered restitution (11%), community service (20%), or urinalysis (25%). We also assessed the number of days in jail that the offender served after sentencing, and 81% did not serve any time in jail.

Dynamic Predictors. The code form also assessed some dynamic indicators of changes in an offender's behavior while on probation. Probation officers were asked whether they filed a violation of probation (VOP) petition for three separate behaviors: noncompliance with treatment, failure to attend scheduled appointments with the probation officer, and noncompliance with an order to refrain from using alcohol or illicit drugs. Probation officers have discretion on whether to file a VOP and generally give the probationer an informal warning for the first incident of noncompliance. Thus, these measures do not capture all of the cases where probationers were noncompliant with probation conditions, but reliably capture the more serious or repeated incidents of noncompliance. All three measures were assessed using a dichotomous variable. A little over one-fifth of the probationers (22%) had petitions filed for treatment noncompliance, 18% were violated for missing scheduled appointments, and 8% were violated for failing to refrain from drinking alcohol or taking illicit drugs.

Outcomes

Violent recidivism was defined as any new arrest for a violent crime while serving their probation sentence. The violent crimes included all of the crimes listed under the description of the sample of violent offenders. Overall, 17.5% of the sample while serving probation committed a new violent crime. The mean number of days sentenced to probation was 615.75 days (sd = 406.71, median = 544 days).

Statistical Procedures

To determine the significant predictors at the bi-variate level, we employed univariate optimal discriminant analysis (UniODA), which provides the maximum possible accuracy in classifying cases and is not based on assumptions about the distribution of the data; it has been used in another study that predicted violent recidivism (Bennett et al., 2000). In order to determine the relative performance of each significant predictor, we used the percentage of total possible improvement in classification accuracy achieved with the predictor—above the classification accuracy achieved through chance alone. This measure is a standardized test statistic called the "effect strength for sensitivity" (ESS).[xi] ESS can range between 0 and 100, where 0 means no improvement in classification accuracy above chance, and 100 means that the predictor explains all variation (errorless classification). Assuming equal sample sizes in the groups to be discriminated, for a dichotomous variable, chance could achieve a mean sensitivity across classes of 50%, and thus this corresponds to an ESS of 0. A mean sensitivity (referring to the average of the percentage correctly classified for nonrecidivists and the percentage correctly classified for recidivists) of 75% across classes lies halfway between chance and perfect performance and corresponds to an ESS of 50% in this example (Yarnold, Soltysik, and Bennett, 1997). Predictors can be ranked as weak, moderate, or strong, based on the ESS. The accuracy in classification above chance performance is considered weak when ESS is less than 25%, moderate when ESS is between 25% and 49%, and strong when ESS is 50% or higher.

Prior research has noted the importance of determining whether significant predictors will generalize to other samples and to the population or whether the significance is due to outliers or other data abnormalities. For each predictor, we conducted a jackknife validity analysis called a leave-one-out (LOO) analysis where classification for each observation is based on all data except the case being classified. LOO analysis is particularly effective at detecting the undue influence of outliers or variations in the cut-off score on a continuous variable. Predictors are generalizable if they have the same accuracy at classifying cases (measured by ESS) in the validity analysis as in the original sample. Thus, significant predictors that will not replicate in a new data set have different ESS's in the original sample and the validity analysis. We report whether a predictor was generalizable or ungeneralizable.

We employed CTA, via optimal discriminant analysis (Yarnold, 1996; Yarnold & Soltysik, in press), to identify the groups that were at high-risk to commit violent recidivism while serving their probation sentence.[xii] We used the hierarchal CTA method in which the tree is started with the generalizable statistically significant predictor that has the strongest ESS, when using all the cases in the sample. At each step the variable with the strongest ESS is entered. In order for the predictor to enter a model or serve as the root (initial) variable of the tree, it had to have the strongest generalizable ESS. Variables that were not generalizable were excluded from entering the CTA model at that step. Partitioning was stopped if there were fewer than 30 cases in a group or there were no additional significant variables that entered the model.

In addition to ESS, we obtained the Area Under the Curve (AUC) performance measure from the Receiver Operating Characteristic (ROC) analysis so that the performance of logistic regression and CTA could be compared. The AUC statistic indicates how well the model performs in comparison to chance at identifying cases of violent recidivism in random pairs of recidivist and non-recidivist cases. AUC ranges from .50 indicating no better than chance performance to 1.00 perfect accuracy. Thus, ESS provides an indication of how well the model classifies observations relative to chance whereas ROC analysis plots sensitivity and 1-specificity pairs that are estimated as the decision threshold is moved from predicting all cases as violent to predicting none of the cases as violent.

Univariate Predictors of Violent Recidivism

Based on bivariate analyses for the entire sample of violent offenders, Table 4.1 presents all of the significant and generalizable predictors of violent recidivism while on probation. In column one of Table 4.1, the value of the variable that is related to a higher risk of violent recidivism is described, and the probability level and ESS are presented in columns two and three respectively. We highlight only the most important findings in the text, and the reader is referred to Table 4.1 for a complete description of all significant and generalizable predictors.

Supporting our hypothesis, the strongest significant predictor was the offender's profile of violent offending, with 29.8% of generalized aggressors committing a new violent crime compared to 17.6% of family only aggressors and 12.2% of non-family only aggressors.

Table 4.1 also reveals that the criminal history measures were stronger predictors than any other category of predictors. Consistent with the prior literature (Gendreau et al., 1996; Hanson & Bussiere, 1998), minorities, single offenders, and male offenders were more likely to commit a new violent crime while on probation. Consistent with the Hanson and Harris (2000)

Table 4.1. Significant and Generalizable Predictors of Violent Recidivism

Significant Predictors of Violent Recidivism	Two-tailed p-value	ESS
Criminal History		
Generalized aggressor	.0001	19.32%
Prior family member violence or no violent crimes	.0001	18.36%
At least one prior arrest for domestic violence	.0001	17.78%
Gang member	.0001	7.34%
Characteristics of the Current Offense		
Current offense is a domestic violence crime	.0001	15.49%
Current offense is violent crime	.001	13.81%
Victim is a family member	.0001	13.55%
Weapon used	.004	9.43%
Female victims or both female and male victims	.046	9.36%
Demographic Characteristics		
Offender is African-American or Hispanic	.0001	14.78%
Offender never married	.034	8.72%
Male offender	.03	5.36%
Annual Income $15,000 or less	.0001	11.87%
24 years old or younger	.009	8.81%
Characteristics of Probation/Treatment		
Court ordered domestic violent/sex offender treatment	.001	10.71%
On standard probation	.001	11.46%
At least two types of treatment ordered/self-referred	.028	7.76%
Self-referred or court-ordered psychiatric treatment	.005	8.98%
Sentenced to some time in jail	.023	7.42%
Characteristics of Behavior While on Probation		
Violation filed for noncompliance with treatment	.0001	10.69%
Violation filed for missed probation appointments	.006	8.65%

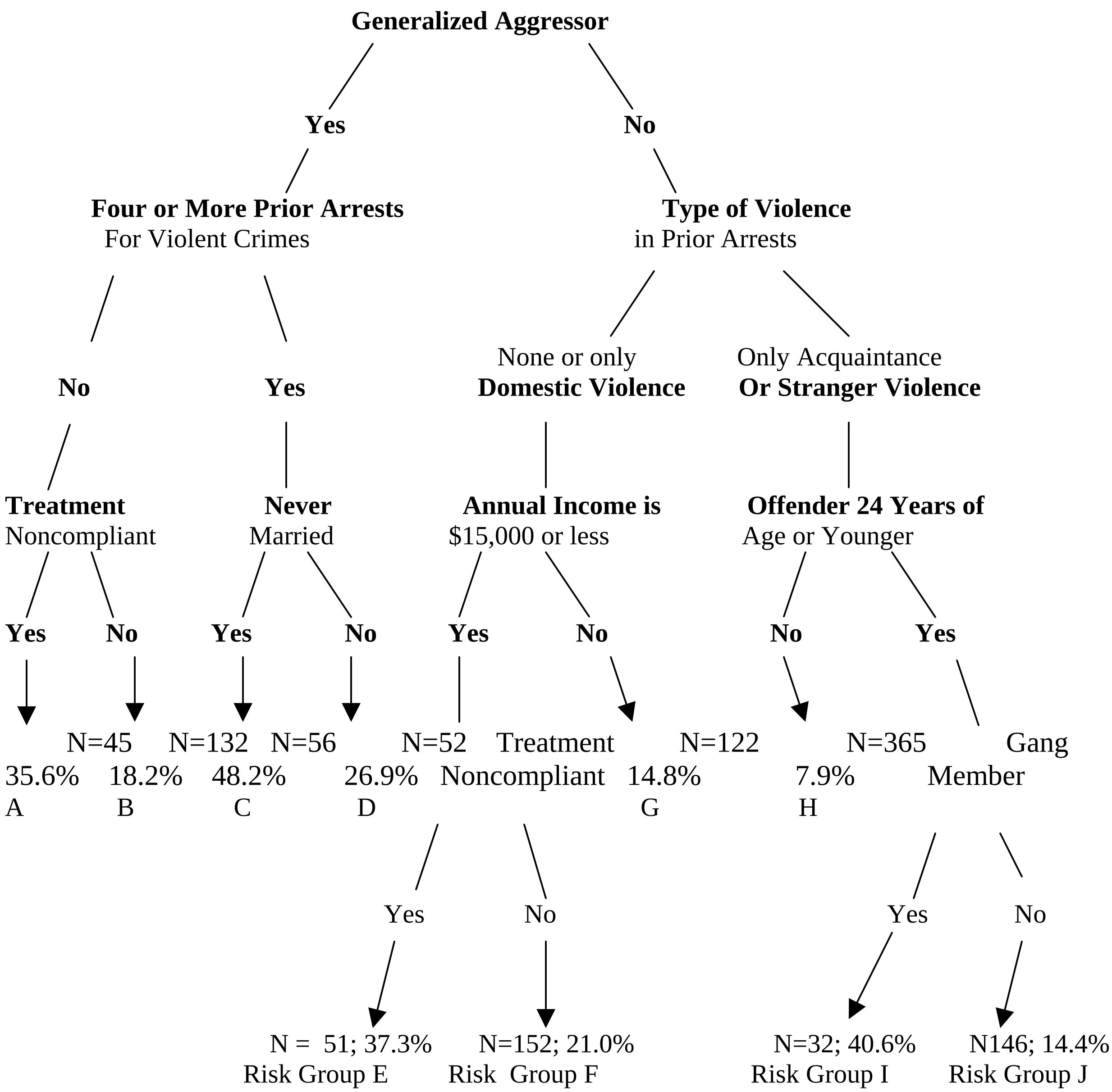
study of sex offenders, violent offenders who committed a new violent offense compared to non-recidivists were more likely to miss scheduled appointments and to be noncompliant with treatment. For the entire sample, these dynamic factors were weaker predictors than the offender's race or criminal history.

CTA Analysis Predicting Violent Recidivism While on Probation

The model was started using the strongest predictor, whether a generalized aggressor or not, and classified 1153 offenders. Figure 1 illustrates the final eight variable CTA model, and the resulting low, medium, and high risk subgroups. Prior research (Steadman et al., 2000) suggested the standard of .5 of the base rate of violent recidivism in the sample (17.5%) as the cutpoint for low risk groups, and twice the baserate of violent recidivism as the cutpoint for high risk groups. Based on this standard and the 17.5% violent recidivism in our sample, violent recidivism of 8.75% and below defines the low risk groups and 35% and higher defines the high risk group. Medium risk is between 8.76% and 34.99%. Figure one identifies the characteristics that define low, medium, and high risk groups; the percentages at the end of each subgroup indicate the percentage in that subgroup that committed a new violent crime while on probation. Using these percentages, practitioners can choose different cutpoints based on their own policies and resource availability. By following the arrows to the endpoints of groups A through J, readers and practitioners can determine in which group an individual offender belongs.

Based on our cut-points, Group H is the only low risk group. Offenders who victimized only acquaintances or strangers and were 25 years of age or older were at low risk of committing violent recidivism. These offenders are likely to be persons who had fights in bars, ball games, and other social places.

Figure 1. **CTA model predicting new arrests for violent crimes while on probation**



Based on the established standard, the CTA model was able to create a high-risk group every time it predicted new arrests for violent crime. Groups A, C, E, and I in Figure 1 are high-risk groups. There are two high-risk groups for generalized aggressors: (a) those who had three or fewer prior arrests for violent crimes and were noncompliant with treatment, and (b) those who had never been married and had four or more arrests for violent crimes. Family only aggressors who earned $15,000 or less annually and were noncompliant with treatment also are at high-risk of violent recidivism. Non-family only aggressors who are 24 years of age or younger and a member of a gang are also at high-risk, with 40.6% having a new arrest for a violent crime while serving their probation sentence.

Bootstrapped Analysis of CTA model

To validate the CTA model, bootstrap analysis (1000 iterations, 50% resample) was conducted on the final model, and 95% confidence intervals for model performance indices were constructed using Tchebysheff's Theorem based on bootstrap results, in order to estimate the potential cross-generalizability of the model if it were to be applied to classify an independent random sample of subjects (Efron & Tibshirani, 1993). The bootstrapped results are presented in Table 2 and show the amount of shrinkage that is expected if the model were applied to a new set of data. As shown in Table 4.2, the bootstrapped 95% confidence intervals are quite small for each endpoint of the CTA tree. The largest confidence interval width is 1.4 percentage point and most endpoint bootstrapped confidence intervals are less than one percentage point in width. The bootstrapped results provide cross-validation evidence that the CTA model will replicate when new samples of data are used.

Table 2. Bootstrappped 95% Confidence Intervals

for the Classification Tree Model Risk Groups

Risk Group	Original Percentage of New Arrests for Violent Crimes	Bootstrapped Mean Percentage of New Arrests for Violent Crimes	95% Confidence Interval	
			Lower	Higher
C	48.2	48.1	47.5%	48.7%
I	40.6	40.6	39.9%	41.4%
E	37.3	37.4	36.8%	38.0%
A	35.6	35.1	34.5%	35.7%
D	26.9	26.5	25.9%	27.1%
F	21.0	21.0	20.7%	21.3%
B	18.2	18.1	17.7%	18.4%
J	14.4	14.5	14.2%	14.9%
G	14.8	14.7	14.4%	14.9%
H	7.9	7.8	7.8%	7.9%

Comparison of the Performance of CTA and Logistic Regression

To determine whether CTA or logistic regression provides more optimal classification accuracy, we also performed a stepwise logistic regression using all 54 predictors. The final logistic stepwise regression model included nine variables. We also conducted a second logistic regression that included an interaction term between generalized aggressor and total number of prior arrests for violent crimes. The odds ratio and unstandardized coefficients for the predictors in the final logistic models are presented in Table 4.3.

One indication of performance is how many cases are classified in the low and high risk group. Based on the established cutpoints for low (8.75% and lower) and high (35% and higher) risk groups in the CTA model, the logistic regression model classified 21.7% of the cases as low risk and 10.9% of the cases as high risk: 32.6% of the cases classified in either the low or high risk group. By comparison, the CTA model classified 31.7% as low risk and 15.9% as high risk

Table 4.3. Logistic Regression Models predicting violent recidivism while on probation

Predictors	Logistic Regression Model without interaction		Logistic Regression Model with interaction	
	b	odds ratio	b	odds ratio
Generalized aggressor	$.53^{*}$	1.69	-.19	.82
Prior arrests for violent crimes	$.16^{***}$	1.17	.04	1.04
On probation for a violent crime	$.74^{***}$	2.09	$.68^{***}$	1.98
Minority race	$.44^{**}$	1.56	$.44^{**}$	1.56
Offender is 24 years old or younger	$.38^{*}$	1.46	$.38^{*}$	1.46
Noncompliant with treatment	$.37^{*}$	1.45	$.37^{*}$	1.45
Annual income less than $15,001	$.40^{*}$	1.49	$.39^{*}$	1.48
Served prior probation term	-.34	.71	$-.32^{t}$	.73
Gang member	$.80^{**}$	2.25	$.84^{**}$	2.31
Generalized aggressor and prior arrests for violent crimes			$.32^{*}$	1.38
Constant	-3.00		-2.83	
Model Chi-square	99.13^{****}		103.86^{****}	

$p < .05$; ** $p < .01$; *** $p < .001$

for a total of 47.6% classified as either high or low risk. By this standard, CTA is superior, classifying 68% more cases than logistic regression in either the high or low risk group.

In addition, Table 4.4 provides a comparison of the models on several performance statistics. On the measure of Area under the curve from the ROC analysis, the logistic models and CTA models have overlapping 95% confidence intervals indicating similar performance even though the AUC from the logistic model is slightly higher than the AUC from the CTA model.[xiii] The ESS statistic is an important indicator of which model is more informative because it assesses how well the statistical model performs relative to chance performance in accurately classifying all observations. The CTA model explained 23.6% of the classification accuracy beyond chance performance whereas the logistic model explained only 9.2%. The logistic model showed very poor performance at accurately classifying offenders that were arrested for a new violent crime (sensitivity = 9.8%) whereas the sensitivity of the CTA model was 35.2%. The logistic model classified 98.7% of the cases that were not arrested for a new violent crime whereas the CTA had a specificity of 88.4%. The logistic model has a higher overall classification accuracy than the CTA, but it does not provide a very good balance between specificity and sensitivity. When all of these measures are considered together, the CTA model is superior to the logistic model if the goal is to predict violent recidivism with the highest possible accuracy above chance performance and to balance the number of false positives and false negatives. CTA provided 30% improvement in classification accuracy above chance performance and classified over three times the number of violent recidivists.

Table 4.4 Comparison of Logistic Regression and CTA models on Performance Measures

Performance Measures	CTA Model	Logistic Model Without interaction	Logistic Model With interaction
ESS	23.6%	8.46%	7.74%
Bootstrapped ESS	25.2%		
ROC	.67*	.71*	.71*
Lower and upper bound ROC	.63 to .71	.67 to .75	.67 to .75
% classification accuracy of violent recidivism cases (Sensitivity)	35.2%	9.8%	8.84%
Bootstrapped Sensitivity	35.6%		
% classification accuracy of non-recidivism cases (Specificity)	88.4%	98.7%	98.9%
Bootstrapped Specificity	88.3%		
Total % classification accuracy (PAC)	78.6%	81.8%	81.8%
Bootstrapped PAC	78.6%		

*$p < .0001$ for Area under the curve statistic of the ROC Curve

General Recidivism

We first conducted UniODA analyses with LOO validity analyses to assess the predictors of being arrested for any new crime while on probation (general recidivism); in the entire sample, 48.8% were arrested for a new crime while on probation. Table 4.5 describes the significant and generalizable predictors, and the value listed in the row is the one related to a higher risk of general recidivism.

Table 4.5. Significant and Generalizable Predictors of General Recidivism While on Probation

Significant Predictors of General Recidivism	p-value	ESS
Prior Criminal History		
Total number of prior arrests greater than five	.0001	20.87%
At least one arrest for a drug crime	.0001	18.01%
At least one arrest for a property crime	.0001	15.51%
Prior arrests for domestic violence and non-family violence	.02	7.29%
At least one prior arrest for driving while intoxicated	.05	3.16%
Characteristics of Current Offense		
Current offense is not violent	.0001	10.22%
Offender victimized more than one victim	.0001	8.45%
Demographic Characteristics		
Offender never married	.0001	21.27%
Offender is African-American or Hispanic	.0001	20.28%
Unemployed	.0001	18.71%
Did not complete high school	.0001	16.05%
Age of offender is 24.5 years or younger	.0001	14.70%
No children living with offender	.007	7.77%
Living with family or friends	.002	6.26%
Male offender	.042	3.74%
Offenders' Mental Health and Substance Abuse		
Offender currently taking at least one illicit drug	.0001	18.99%
Previous history of alcohol abuse	.018	7.12%
Characteristics of Probation/Treatment		
Court sentenced offender to serve some jail time	.0001	10.04%
Court ordered urinalysis	.0001	8.01%
Court ordered community service	.004	6.70%
At least two types of treatment ordered/self-referred	.035	5.09%
Characteristics of Behavior While on Probation		
Violation filed for missed probation appointments	.001	16.85%
Violation filed for noncompliance with treatment	.0001	15.45%
Violation filed for substance abuse	.0001	6.50%

Whereas few demographic characteristics predicted violent recidivism, nine demographic characteristics were significant and generalizable predictors of general recidivism. The three strongest demographic measures, each explaining over 20% of the accuracy in classification beyond the improvement by chance, were annual income, marital status, and race. Prior research has found that these measures are consistently significant predictors of general recidivism (for a review see Hanson & Bussierre, 1998).

<u>CTA Model for General Recidivism</u>

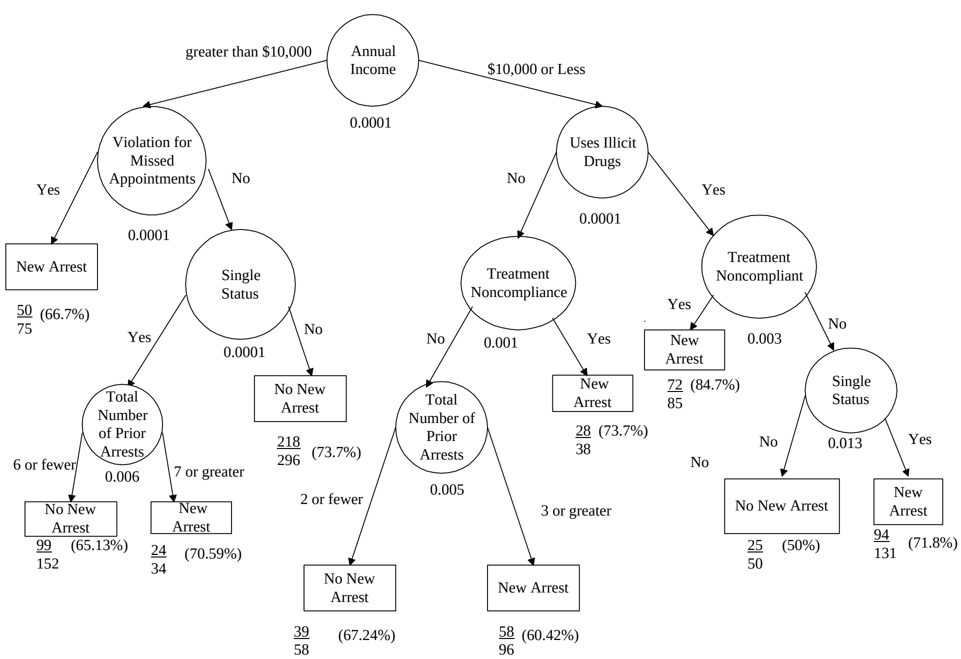
The CTA analysis predicting general recidivism started with annual income, which was the strongest predictor of general recidivism, and resulted in a nine variable CTA model that showed moderate performance (ESS = 39.1%) and had an overall classification accuracy of 69.6%. Of those offenders who were arrested for a new crime, 65.1% were accurately classified, and 74.1% of offenders who were not arrested were accurately classified.

We also conducted a second CTA analysis starting with generalized aggressor or not. The analysis resulted in a 12 variable model that showed moderate performance (ESS = 39.3%) and had an overall classification accuracy of 69.7%. Of those offenders who were arrested for a new crime, 65.2% were accurately classified and 74% of offenders who were not arrested were accurately classified. This model shows almost identical performance with the income CTA model exception that the income model is more parsimonious. Parsimony is an important rule of science; it means that the most simplest model or theory should be accepted if it can explain the outcome as well as a more complex model. Thus, the income model is better in that it is more parsimonious. In the generalized aggressor model, there are three groups of generalized aggressors who are at a high risk of being arrested for a new crime: (1) those with treatment noncompliance; (2) those with prior arrests for drug crimes; (3) those who served time in jail.

There also are three groups of family only or non-family only aggressors who are at high risk: (1) those living in poverty who are on probation for a nonviolent crime; (2) those living in poverty who are on probation for a violent crime and are being noncompliant with treatment; and (3) high school drop outs making more than $10,000 annually and using illicit drugs. For family and non-family only aggressors, income and education are important static predictors and using illicit drugs and treatment noncompliance are important dynamic predictors.

Figure 2 presents the CTA model beginning with income. Offenders with annual incomes of $10,000 or less and offenders who earned more than $10,000 annually have some different predictors of general recidivism. Treatment noncompliance and use of illicit drugs are significant predictors for those offenders earning $10,000 or less annually whereas violations for missed appointments is a significant predictor for those that earn more than $10,000 annually.

Figure 2. CTA Model Predicting General Recidivism



For both income groups, total number of prior arrests and single status are significant predictors of general recidivism. Overall, prior arrests is less important than the other variables in that it classifies the fewest number of offenders, but it is used to classify both offenders who earn less than $10,000 and those that make more than $10,000.

For those earning $10,000 or less annually, there were two high risk groups: (a) those who were treatment noncompliant and (b) single offenders using illicit drugs. Additionally, offenders in this income group who were compliant with treatment and did not use drugs were almost twice as likely to be arrested for a new crime if they have three or more prior arrests compared with if they had two or fewer prior arrests.

Offenders earning more than $10,000 annually are at high risk of general recidivism if they are violated for missing scheduled appointments with their probation officer or are single offenders who have seven or more prior arrests.

<u>Predictors of Unsatisfactory Discharge From Probation</u>

We performed bi-variate analyses using optimal discriminant analysis to determine the significant predictors of unsatisfactory discharge, and a LOO analysis to determine if the significant predictors were generalizable or not. In column one of Table 4.6, the value of the generalizable predictor that is related to a higher risk of unsatisfactory discharge is described, and the probability level and ESS are presented in column two and three respectively. We highlight only the most important findings in the text, and the reader is referred to Table 4.6 for a complete description of all significant and generalizable predictors.

The strongest predictor of unsatisfactory discharge was new arrest for any crime, and this predictor explained almost 43% of the classification accuracy beyond the improvement of classification accuracy achieved by chance alone. A new arrest for a violent crime also was a significant and generalizable predictor, but was substantially weaker than a new arrest for any crime. The filing of petitions to revoke probation for noncompliance with treatment, missing scheduled appointments, and abusing alcohol or drugs also were related to unsatisfactory discharge. These dynamic predictors were much stronger predictors of unsatisfactory discharge than prior criminal history, offense characteristics, or demographic or background characteristics.

Table 4.6 Significant and Generalized Predictors of Unsatisfactory Discharge from Probation

Significant and Generalized Predictors	p-value	ESS
Dynamic Factors: Behavior Changes while on probation		
New arrest for any crime	.0001	42.96%
Violation filed for noncompliant with treatment	.0001	32.74%
Violation filed for noncompliant with scheduled appointments	.0001	24.73%
New arrest for a violent crime	.0001	17.72%
Violation filed for substance abuse	.0001	11.79%
Administrative sanction	.0001	7.67%
Demographic Variables		
Unemployed or out of labor force	.0001	23.04%
African-American or Hispanic offender	.0001	19.60%
Did not graduate from high school	.0001	18.32%
Single	.0001	14.96%
Not living with any children	.01	8.37%
Living with family or friends	.007	6.55%
Substance Abuse		
Previous or current alcohol abuse	.0001	13.58%
Probation and treatment conditions		
Two or more treatments ordered or self-referred	.0001	11.27%
At least one treatment ordered	.002	9.36%
Restitution required	.009	5.17%
Offender ordered to undergo urinanalysis	.0001	9.78%
On specialized probation	.001	9.96%

Minorities, unemployed offenders, high school dropouts, and never married offenders also were at a higher risk of unsatisfactory discharge. Offenders who used or abused alcohol were at a higher risk of unsatisfactory discharge. Five conditions of probation also were related to unsatisfactory discharge. Offenders ordered into treatment were more likely to be discharged unsatisfactorily than offenders who were not ordered into treatment. Interestingly, criminal history predictors were not significant and generalizable predictors of unsatisfactory discharge.

Classification Tree Analysis Predicting Unsatisfactory Discharge

We wanted to determine the static predictors after controlling for a new arrest while on probation so we did not allow violation of petitions filed for noncompliance, missing scheduled appointments or abusing alcohol or drugs to enter the CTA model.

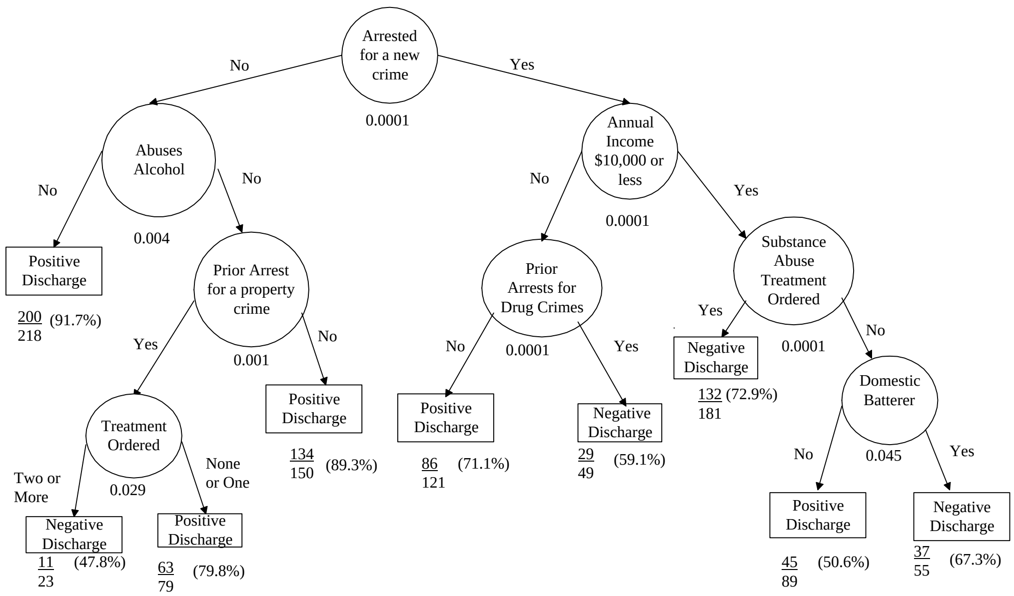
The final CTA model contained eight predictors and showed moderate performance (ESS = 46.3%). It had an overall classification accuracy of 73%, and accurately classified 61.8% of the unsatisfactory discharged cases and 84.2% of the satisfactory discharged cases. The model began with the strongest predictor, whether the offender was arrested for any new crime while on probation. Thus, the model provides the significant predictors for those who had a new arrest while on probation and for those who did not have a new arrest while on probation.

There was only one high risk group for offenders that did not have any new arrests while on probation: those who abused alcohol, were ordered into two or more different types of treatment, and had a prior arrest for a property crime. Three groups of offenders had a very low chance of negative discharge if they were not arrested for a new crime while on probation: (a) did not currently or previously abuse alcohol; (b) currently or previously abused alcohol, but did not have any prior arrests for property crimes; and (c) currently or previously abused alcohol, had a prior arrest for a property crime, but were not ordered treatment or ordered into only one program.

There were three high risk groups for offenders that were arrested for a new crime while on probation. Almost 73% of offenders who earned less than $10,000 and were ordered to undergo substance abuse treatment had a negative discharge. A little over two-thirds of the domestic batterers who earned less than $10,000 annually and were not ordered to undergo substance abuse treatment had a negative discharge. Offenders who were arrested for a new crime, earned more than $10,000 annually and had prior arrests for drug crimes had a 59% chance of a negative discharge.

Knowing the characteristics of offenders who were arrested for a new crime, but had a positive discharge from probation provides some information about the criteria that probation officers and judges use to make decisions about filing probation petitions and revoking probation. Offenders had over a 70% chance of a positive discharge if they were arrested for a new crime, earned more than $10,000 annually, and had no prior arrests for drug crimes. Half of the offenders who committed violence against acquaintances or strangers, earned less than $10,000 annually, were not ordered into substance abuse treatment and were arrested for a new crime while on probation were given a positive discharge from probation.

Figure 3. CTA Model Predicting Unsatisfactory Discharge of Probation



Conclusion

To our knowledge, we are the first to examine how best to combine dynamic and static predictors to obtain optimal accuracy in predicting violent and general recidivism of violent offenders while they are on probation. This paper demonstrates the importance of separating generalized aggressors, family only aggressors, and non-family only aggressors in research on the predictors of violent recidivism. Supporting research on the typologies of domestic batterers (e.g., Saunders, 1993; Tweed & Dutton, 1998), generalized aggressors had more extensive criminal histories than family only and non-family only aggressors. Whether offenders were generalized aggressors or not emerged as the strongest predictor of violent recidivism, and also a significant, though weaker predictor of general recidivism. The number of prior arrests and alcohol abuse were important risk factors of violent recidivism for generalized aggressors, but did not predict the risk of violent recidivism for the other two groups of violent offenders.

Treatment noncompliance, however, was an important risk factor for generalized aggressors and family only batterers.

These findings indicate that risk assessment tools tailored to generalized aggressors, family only aggressors, and non-family only aggressors may provide greater accuracy in the prediction of violent recidivism. Our analyses also demonstrate that CTA compared to logistic regression is more accurate and informative at predicting violent recidivism. The logistic regression model predicted with substantial accuracy those who were not arrested but was very inaccurate at predicting those who were arrested for a violent crime. Furthermore, the logistic model was inadequate at balancing the accuracy of predicting those who were not arrested and those who were arrested.

Consistent with prior research (e.g., Hanson & Bussiere, 1998; Bonta, Law & Hanson, 1998), single status and annual income are stronger predictors of general recidivism than the other variables in the CTA model, although all the variables in the model classify a substantial proportion of the offenders. Prior arrest history is a significant predictor of general recidivism only for single offenders who comply with probation conditions; this finding suggests that compliant behavior while on probation may indicate a lower risk of recidivism only for those with few prior arrests. Offenders with extensive criminal histories may appear to be complaint, but may continue with their criminal lifestyle when they believe they will not be detected.

One limitation of our study is that the use of prior official criminal history and current offense to classify offenders into one of the three groups may misclassify non-family only aggressor group. Domestic battery is often not reported to the police; therefore, some non-family only aggressors may have committed domestic violence and should have been classified as generalized aggressors. Interviews with significant others and family members may help in classifying offenders into one of the three groups of violent offenders. The fact that type of offender was the best predictor of violent recidivism, however, suggests that most of the offenders were correctly classified.

Our study used a large representative sample of violent offenders on probation throughout one state, which provides more confidence that these results transcend jurisdictions. Because we employed only predictors commonly available to probation officers, the results provide information that probation officers can easily use to assist in their risk predictions and decisions to adjust monitoring in an attempt to prevent future crime. Future research, however, should assess whether information about the offender's childhood background and personality and mental health disorders can increase the accuracy of predicting violent recidivism. In conclusion, the high risk characteristics of generalized aggressors, family only aggressors, and non-family only aggressors deserves further exploration through analyses that allow different risk factors to emerge for each group of violent offenders.

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Endnotes

[i]

[ii] Illinois Bail Bond is a specific law that requires offenders charged with domestic battery or other domestic violence crime to refrain from contact with the victim for 72 hours or their bail bond is revoked.

[iii] There were 41 sex offenders who were not included in the sample because there are different predictors of sex offender's violent recidivism.

[iv] A separate analysis of domestic violence and non-domestic violence violent offenders found that 71.4% of domestic violence violent offenses were misdemeanors compared to 39.3% of non-domestic violent violent offenders.

[v] Eighty percent of the domestic violence violent offenses involved a female victim compared to 37% of non-domestic violence violent offenders. Similarly, 88.6% of sex offenses involved a female victim.

[vi] The formula for the effect strength of sensitivity is ESS = (1 – {(1 – mean sensivity across classes)/100 – 100/C))}) x 100%. C is the number of response categories for the class variable (e.g., violent recidivism) (Yarnold, Soltysik, & Bennett,1997).

[vii] Classification Tree Analysis (CTA) has been shown to have better predictive and classification accuracy than alternative linear (logistic, discriminant analysis, stepwise OLS regression) and nonlinear (CHAID, CART) statistical classification methodologies (Soltysik & Yarnold, 1993; Soltysik & Yarnold, 1994; Yarnold, 1996; Yarnold & Soltysik, 1991). It uses an algorithm that maximizes accuracy.

[viii] Employment also had a similar level of predictive accuracy for offenders ordered into substance abuse treatment with 70% of unemployed or retired offenders accurately classified as treatment failures and 26.2% of employed offenders accurately classified as treatment failures.

[ix] Illinois Bail Bond is a specific law that requires offenders charged with domestic battery or other domestic violence crime to refrain from contact with the victim for 72 hours or their bail bond is revoked.

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[xii] **In preliminary research CTA via ODA has consistently yielded better predictive and classification accuracy than alternative linear (logistic, discriminant analysis, stepwise OLS regression) and nonlinear (CHAID, CART) statistical classification methodologies (Arozullah et al., 2000; Arozullah et al., in press; Mueser et al., 2000; Soltysik & Yarnold, 1993; Soltysik & Yarnold, 1994; Yarnold, 1996; Yarnold & Soltysik, 1991; Yarnold, Soltysik, & Bennett, 1997). This is not surprising, since CTA uses an algorithm that explicitly maximizes accuracy rather than likelihood or variance.**

[xiii]Due to tied values in the dataset, the AUC statistic may be biased, which the SPSS program noted. ROC curves were originally designed to handle dichotomous, nonparametric data. Thus, the reader should not place too much importance on this one statistic.