MULTIVARIATE ACTUARIAL PREDICTION OF FELONIOUS RECIDIVISM OF MALE PAROLEES: DEVELOPEMENT AND CROSS-VALIDATION OF A SERIES OF RISK ASSESSMENT MODELS USING STEPWISE LOGISTIC REGRESSION

By

Richard Alfred Bradshaw

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Counseling,
Educational Psychology and Special Education

1987

ABSTRACT

MULTIVARIATE ACTUARIAL PREDICTION OF FELONIOUS RECIDIVISM OF MALE PAROLEES: DEVELOPMENT AND CROSS-VALIDATION OF A SERIES OF RISK ASSESSMENT MODELS USING STEPWISE LOGISTIC REGRESSION

By

Richard Alfred Bradshaw

Three variables have been identified as the most stable, effective predictors of criminal recidivism: criminal history, substance abuse history, and age. A fourth predictor, current offense, was included in the study because it had been used in many recidivism prediction devices with reasonably good results. Operational measures of recidivism on parole include: arrest for violent felony and arrest for general (violent or nonviolent) felony. Predictors and measures of recidivism on parole over a 2 1/2 year follow-up period were obtained from criminal files and records of state police and parole departments.

For split samples of 317 and 323 male parolees, predictors were combined into two series of multivariate equations using stepwise logistic regression. Two equations were constructed to predict arrest for violent felony and four were developed to predict arrest for general felony. Each regression was constructed on one subsample and cross-validated on the other.

Across both subsamples eight operational measures of criminal history were significantly related with general felonious recidivism but no measures were related with violent felonious recidivism, likely due to the relatively low base rate of violent recidivism on parole. Neither current offense nor substance abuse history were related to recidivism on parole, but age was negatively related with general felonious recidivism.

None of the six regression models, when cross-validated were found to equal or exceed most current actuarial risk prediction instruments, in terms of predictive accuracy or efficiency.

This dissertation is dedicated to my wonderful wife, Phyllis, whose wisdom I have grown to appreciate more than ever during my doctoral studies; and to my loving parents, Richard and Marie Bradshaw. My father died just prior to completion of this project but I continue to feel his encouragement and support.

ACKNOWLEDGEMENTS

I would like to thank Drs. William Farquhar and Fred Pesetsky for their encouragement in this project and their recommendations for the Graduate Research Fellowship Grant from the National Institute of Justice. I would also like to thank Dr. William Mehrens for his willingness to be on my committee and attend a defense during his sabbatical.

Between the dissertation proposal meeting and the final oral defense, Dr. Terry Allen died. I very much appreciated his support in this project, particularly during the early stages. I would like to express my gratitude to Dr. Robert Trojanowicz for his willingness to replace Dr. Allen at a late stage in this project.

Finally, the high quality of this manuscript is a testament to the skill, hard work and perseverance of Fay Oko.

TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

Table		Page

Table		Page
5.18	Relationships between operational measures of age and the criterion measure 'arrest for general felony on parole'	160
5.19	Summary of stepwise results for three logistic regressions using subsample I for construction	162
5.20	Summary of stepwise logistic regressions, with coefficients for each term from the final step, using subsample I for construction	163
5.21	Summary of stepwise results for three logistic regressions using subsample II for construction	167
5.22	Summary of stepwise logistic regressions, with coefficients for each term from the final step, using subsample II for construction	168
5.23	Summary of predictive accuracy statistics computed for construction and cross-validation samples for all six logistic regressions . . .	171

LIST OF FIGURES

Figure		Page

CHAPTER I

Introduction

The problem in this study involves assessment of the validity of multivariate actuarial behavior prediction models developed using stepwise logistic regression. Criteria being predicted are measures of both violent and general felonious recidivism.

The following information is provided for the reader in this chapter: (a) definition of terms, (b) significance of the study, (c) delimitations, (d) limitations, and (e) general hypotheses.

Definitions of Terms

Since the content area of this study involves criminology, it was considered appropriate to define a number of criminal justice terms in addition to providing specific definitions of more general psychological terms, as they are used in this study.

Actuarial. "...statistical prediction (which) refers to the establishment of statistical relationships between given predictor variables (e.g., age, number of prior offenses) and the criterion.
...The prediction variables may include clinical diagnoses or scores on psychological tests, but these are statistically weighted in a prediction formula" (Monahan, 1978, p. 257).

Arrest. "Taking a person into custody by authority of law, for the purpose of charging him with a criminal offense or for the purpose of initiating juvenile proceedings" (SEARCH Group, Inc., 1976, p. 14).

Calendar time. Actual time, in months or years, between two events; in contrast to "street time".

Charge. "A formal allegation that a specific person has committed one or more specific offenses" (SEARCH Group, Inc., 1976, p. 21).

Current offense. The conviction(s) for which a parolee was incarcerated prior to current release on parole.

Conviction. "A judgement of a court, based either on the verdict of a jury or a judicial officer or on the guilty plea of the defendant, that the defendant is guilty of the offense(s) for which he has been tried" (SEARCH Group, Inc., 1976, p. 25).

Felony. "A criminal offense punishable by death or by incarceration in a state or federal confinement facility for a period of which the lower limit is prescribed by statute in a given jurisdiction, typically one year or more" (SEARCH Group, Inc., 1976, p. 48).

Misdemeanor. "An offense usually punishable by incarceration in a local confinement facility, for a period of which the upper limit is prescribed by statute in a given jurisdiction, typically limited to a year or less" (SEARCH Group, Inc., 1976, p. 62).

Plea bargaining. "The exchange of prosecutorial and/or judicial cobcessions, commonly a lesser charge, the dismissal of other pending charges, a recommendation by the prosecutor for a reduced sentence, or a combination thereof, in return for a plea of guilty" (SEARCH Group, Inc., 1976, p. 70).

"Rap" sheet. Police record of prior contacts with the legal system, including arrests, charges, convictions and sentences.

Recidivism. "The repetition of criminal behavior; habitual criminality" (SEARCH Group, Inc., 1976, p. 78). The term is restricted in this study to such behavior only as it occurs during a 2 1/2-year follow-up period from the date of release on parole.

Risk assessment. The process or product of actuarial prediction of criminal recidivism.

<u>Street time</u>. Actual or "calendar" time (in months or years) between two events, excluding time spent in prison, jail or any other correctional facility.

<u>Violent felony</u>. Includes any of the following offenses: murder, attempted murder, rape, attempted rape, sodomy, aggravated kidnapping, kidnapping, aggravated robbery, robbery, attempted robbery, extortion, aggravated burglary, felony assault, aggravated assault, terrorism, arson of a dwelling or arson (Fischer, 1985, p. 36).

Significance of the Study

This section of the chapter includes information substantiating the need for the study, the uses of recidivism prediction and the alternatives to actuarial prediction of recidivism.

Need for the Study

Gottfredson (1967), one of the leading criminologists in the United States, stressed the importance of prediction in the following statement:

> Prediction, a traditional aim of science, is a requisite to any effective crime and delinquency prevention or control program. If we seek to control delinquent and criminal behavior, then first we will need to be able to predict it. (p. 171)

It has been stated by experts in criminal justice that the very essence of parole is risk prediction (Dietz, 1985) and that parole cannot exist without the protection of risk prediction (Smith & Berlin, 1979):

> In the large states like New York, Michigan and California, about 90 percent of the prisoners are paroled, while in the United States "more than 60 percent of adult felons for the nation as a whole --are released on parole prior to expiration of their sentences." It is therefore of the utmost importance not only to society, but to the lawbreaker as well, to determine which prisoner is a good parole risk after serving what portion of his sentence. (p. 86)

Peay (1982) continues, in the same vein:

> ...an individual "has as much right to remain unmurdered, unmugged and unraped as he or she does to avoid unjust incarceration as a falsely positive case of dangerousness. (p. 219)

Several developments since 1970 have spurred the increased interest in, and application of, parole recidivism prediction, including: (a) lawsuits against parole boards for failing to apply prediction to prevent violent crimes of parolees (Bonham, Janeksela, Bardo & Iacovetta, 1984); (b) the Tarasoff v. Regents of the University of California (1976) decision to hold psychologists liable for failing to make predictive assessments of "dangerousness" and warn potential or intended victims; and (c) the development of a prison overcrowding crisis to which solutions such as selective parole are sought. Crime by parolees and prison overcrowding are discussed further in the following two subsections, as they relate to recidivism prediction.

<u>Crime committed by parolees</u>. An increase in violent crime since 1970, particularly offenses committed by parolees, has been documented in a number of sources recently. The following statements by Thompson (1982) and Haig (1981), respectively, attest to this phenomenon:

> At this point in our history, the threat of violent crime has reached epidemic proportions. The statistics have gone off the charts; and it does not require a litany of shocking examples to recognize that each crime statistic represents a victimized human being, a shattered life, or a

> broken family. The time has come to take a unified approach to the problem of violent crime. The magnitude of the threat to our domestic tranquility requires a consensus reaction. (p. 867)
>
> In the past five years 72 Canadians were killed by convicts free either on parole or mandatory supervision. That's more than one Canadian killed every month from 1975 to 1980 under the auspices of a federal government...
>
> There simply must be more stringent regulations imposed to govern the release of violent and potentially violent criminals. (p. 10)

Prison overcrowding. The October 5, 1984 issue of the Michigan Department of Corrections newsletter (State of Michigan, 1984) noted the following trends relative to the prison population:

> The department anticipates a record 7,500 prison commitments by the end of 1984. This, coupled with a rapidly-increasing average sentence length will result in a serious prison overcrowding problem.
>
> The department's Program Bureau recently completed an analysis of prison commitments this year and has concluded that the growth is so great that the Prison Overcrowding Emergency Powers Act (EPA) will no longer allow us to reduce population to capacity as was its intent.
>
> Next year the department predicts we will be 1,000 beds short... (p. 1)

The phenomenon described above is being reported throughout the United States, as evidenced in the following quoted statement by Thompson (1982):

> The problem of available bed space in our state prisons is the single most significant criminal justice issue in the country today. It is a problem that the states no matter how hard they try, are virtually incapable of solving themselves. (p. 868)

Millard and Brown (1985), in speaking with the new director of the National Institute of Corrections, asked the question, "What do you feel is corrections' greatest problem today?" to which he responded: "Probably overcrowding because of all the things that happen as a result of it, and how it affects the entire criminal justice system" (p. 70).

Towberman (1984) and Forst, Rhodes, Dimm, Gelman and Mullin (1983), respectively, comment on the role that improved prediction of parole recidivism could play in alleviating the current prison overcrowding crisis:

> In an era of overcrowded jails and prisons, virtually all observers agree that the major efforts of correctional agencies should be to identify and protect the public from violent offenders. (p. 142)
>
> A strategy of allocating scarce federal resources disproportionately to cases involving the most active and dangerous recidivists offers the potential for both crime reduction and reduction in prison and jail populations, in both Federal and local jurisdictions. (p. 17)

Paul Stageberg, Executive Committee Chairperson of the Criminal Justice Statistics Association, noted that 25 states and the federal government sent representatives to risk assessment workshops sponsored by the Criminal Justice Statistics Association (Stageberg, 1983) and that 15 states currently use parole prediction instruments. When a new parole recidivism prediction device is released, with claims of predictive accuracy superior to instruments which preceded it, parole boards in every state and the federal government are open for lawsuits, claims that criminal acts of parolees could have been prevented, had the new instrument been applied.

Uses of Recidivism Prediction

Both Gottfredson (1967) and Zwanenberg (1977) note that recidivism prediction can be used on either individual (micro) or societal (macro) scales. On a macro scale it can be used to assess criminal justice population trends to assist in policy formulation. Stageberg (1983) lists a number of applications at the level of individual offenders, including : (a) identifying which parolees can safely be put on minimum supervision, or "paper" caseloads; (b) reducing prison populations while increasing public protection; (c) determining "true" program effectiveness by equalizing treatment populations for recidivism risk; and (d) screening out higher-risk clients from new programs until they are established.

Alternatives to Actuarial Prediction of Recidivism

A number of difficulties and shortcomings of actuarial prediction of recidivism are identified in the methodological and statistical developments section of the review of literature (Chapter III). Because of these problems, a number of leaders in the field of criminal justice have promoted (a) a return to subjective assessments of risk, and (b) emphasis on determinate and "just desserts" sentencing practices. The weaknesses of these alternatives to actuarial prediction of recidivism are identified in the following two subsections.

Subjective assessments of risk. Critics of actuarial prediction techniques have emphasized that large numbers of "false positives" (prediction errors) result from such procedures. What many of these individuals do not realize is that the superiority of actuarial (statistical) techniques over clinical (subjective) predictions has been consistently demonstrated over a period of many years (see subsection of Chapter III on clinical versus actuarial prediction). Both Wilkins (1980) and Forst and his colleagues (1983) have stressed that more false positives are almost certain to result from conventional (subjective) targeting strategies than from those based on empirically-derived criteria.

Determinate sentencing and "just desserts" policy. Indeterminate sentencing allows for reduction or extension of sentences for particular crimes based on (a) criminal histories of offenders, and (b) predicted "dangerousness" or recidivism risk to society, upon release. Sanchez (1984), Wainer and Morgan (1982), and von Hirsch and Gottfredson (1983-84) state that current predictions of recidivism are not accurate enough to base sentencing upon. As a result, determinate, or inflexible, sentencing based on the philosophy that criminals should receive their "just desserts" according to the crimes they are convicted of, has been achieving widespread popularity. The major criticism of this approach is that it relies on determination of the degree of an offender's "moral culpability" for committing a crime which, as Monahan (1984) and the American Psychological Association (1978) have noted, is more difficult to assess than recidivism risk.

Finally, while many false positives do result from actuarial predictions of recidivism, criticisms have addressed only those cases in which selective incapacitation has been applied rather than some form of additional supervision or assistance to offenders. Selective incapacitation is described by Forst and his colleagues (1983):

> The concept of reserving prison and jail space for those offenders who, if released to society, would likely inflict the greatest harm has emerged as a dominant principle of criminal case processing and selection. (p. 10)

Greenwood (1982) is the leading proponent of the use of actuarial prediction to guide selective incapacitation.

Criticism of "just desserts" policy. It is the opinion of the author of this dissertation that actuarial prediction should be used to guide selective employment assistance and community supervision, rather than selective incapacitation. By applying such additional assistance programs rather than additional punishments, high rates of false positives become much less of a problem, since "false positive" offenders will merely receive additional assistance and supervision rather than extended incarceration.

As a result of a good number of years of research in Iowa, Fischer (1980) stated, ". . . better methods of supervision, including more frequent use of residential facilities and halfway houses for high risk probationers and parolees, is recommended" (p. 5). In summarizing and making conclusions regarding a massive empirical study and review of literature in Michigan (State of Michigan, 1978), the following conclusion was drawn:

> For the Department of Corrections, it is recommended that an attempt to resolve parolee employment problems be made; an adequate, secure job is the best deterrent to renewed criminal behavior. (p. xii)

Jenkins' (1984) statement, calling for a return to the original purpose of parole also supports the use of actuarial recidivism prediction to guide assistance in returning to the community rather than applications of extended punishment or early release:

> Parole was not designed to be an expedient for reducing the prison population--it was a means by which the link between custody and community could be properly and carefully re-established. (p. 2)

In summary, this study is significant because of its potential for providing movement toward solutions to major problems in criminal justice today, because of the many uses of actuarial predictions of recidivism, and because the alternatives seem to be poorly founded.

Delimitations

This brief section is intended to delineate the parameters of the present study. Adult criminality, rather than juvenile delinquency, is predicted. Only behaviors qualifying as criminal recidivism constitute criteria to be predicted; No attempt is made to study domestic violence. The study is limited further to behavior upon release on parole. Hence, prediction of recidivism during probation, or forecasts of institutional adjustment are not made. This is also not a study of the more general category of mental health risk prediction which encompasses all "dangerous" behavior. Monahan (1981) drew a distinction between "street crime" and "corporate violence". The present study investigates only the first of these two types of criminality.

Gottfredson (1967) and Zwanenburg (1977) described two major uses of actuarial prediction: (a) individual (micro-level), and (b) societal (macro-level). Only the first of these two levels of application is considered in this study.

The study is further limited to males who were incarcerated in state correctional facilities in Michigan (see map in Appendix B) and released on parole during the calendar year of 1980. The extent of parole follow-up is limited to 2 1/2 years and the recidivism measures and predictors used are limited to those described in Chapter IV.

Limitations

Major limitations of the present study include the facts that: (a) the data used were originally collected (in files) for administrative rather than research purposes and are subject to the shortcomings of such information; (b) the cross-validation procedures applied (using file information reported over a 2 1/2 year follow-up period), are retrospective rather than prospective in nature; (c) apart from interrater coding agreement, no assessment of the reliability of either predictor or criterion variables was possible (data were pre-collected from files); and (d) arrest records used as measures of recidivism are subject to all the limitations of reported offenses, that is, a parolee with no arrest record could have been (i) truly non-criminal, (ii) criminally active but not apprehended, or (iii) criminally active but apprehended in a jurisdiction other than Michigan.

Hypotheses

1. Criminal history of parolees is related to felonious recidivism on parole.
2. Current offense for parolees is not related to felonious recidivism on parole.
3. Substance abuse history of parolees is related to felonious recidivism on parole.
4. Age of parolees is negatively related to felonious recidivism on parole.
5. A logistic regression model developed in the study for predictions of general felony arrest will result in predictions which equal or exceed the accuracy of those reported for other current prediction models.
6. A logistic regression model developed in the study for prediction of violent felony arrest will result in predictions which do not equal or exceed the accuracy of those reported for other current prediction models.

Theoretical and empirical bases for these hypotheses, and rationales for selection of variables in the study are provided in the next chapter.

CHAPTER II

Review of Literature:

I Predictors of recidivism

Selection of Variables for Inclusion in the Study

An extensive body of research and review literature exists pertaining to the prediction of recidivism and violent criminal behavior. While reasonably extensive, the review provided in this proposal does not include more than several articles published prior to 1970. Thorough reviews of the literature from 1923 to approximately 1970 presently exist (Simon, 1971; Gottfredson, 1967; State of Michigan, 1978). These summaries provide an excellent review and critique of relevant literature, highlighting stable, well-replicated findings which have been included in this review of literature.

The literature regarding prediction of criminal violence consistently supports the inclusion of sex, race and marital status as predictor variables. Monahan (1981) reviews these measures briefly and notes that they have been found to be reliable, effective predictors. Since crime statistics consistently report that over 95 percent of those who are charged with criminally violent acts are male (Monahan, 1981), only males are included in the study.

Zwanenburg (1977) has noted that prediction instruments which include race are likely to be questioned, or even attacked, with claims of racial bias and oppression of the poor. Another "controversial" variable found to be useful as a predictor of recidivism has been marital status. Considerable evidence also indicates that if an offender was single (never married) at the time of his last (current) offense, he will be considerably more likely to recidivate on parole than an offender with any other marital status (Murphy, 1980; State of Michigan, 1978). Regarding such variables as race and its inclusion in prediction instruments, Zwanenburg (1977) states the following:

> Simplicity and efficiency must work both ways: to ensure proper use of the instrument and to the one whose behaviour is under scrutiny, to avoid the possible negative effects resulting from the feeling that the prediction (and the subsequent treatment) is just a whimsical affair that is conducted by others far beyond his or her power and comprehension. These requirements sometimes force us to give up items of information with great predictive power, thereby reducing the overall performance of the prediction instrument and its efficacy. (p. 28)

In light of this controversy, logistic regressions were computed both with, and without, race and marital status, to permit future users of these regression equations to choose whether or not predictions include these variables.

In addition to race and marital status, there are essentially four groups or clusters of predictor (independent) variables in this study: criminal history, current offense, substance abuse and a series of age-related variables. The criterion (dependent) variables are violent and general (combined violent and nonviolent) felonious recidivism of parolees. Literature pertaining to each of these core variables is presented in the first section of this review. The second section includes a review of research relative to other variables which, although found to be useful predictors of criminal behavior in many studies, were excluded from explicit invèstigation in this study. These "other" groups of variables include: psychological tests; childhood and family variables; and employment stability. It was considered necessary to provide reviews pertaining to these variables to justify their exclusion, since they have all been found in some studies to be effective predictors of criminal behavior.

A separate chapter of the review of literature includes findings relative to the development of research methods and statistical techniques for prediction of recidivism and violent criminal behavior, and the final section is a review of current criminal risk assessment instruments and recidivism prediction models.

Core Variables in the Study

Criminal History

As with the prediction of many human behaviors, past behavior is the best predictor of future behavior (McCleary, 1978). Regarding the importance and appropriateness of using past behavior to predict future "dangerousness," Peay (1982) made the following statement:

> ...it is possible that the predictive efficacy of such decisions would increase because they would be based on the only criteria which have any

> demonstrated predictive efficacy, namely thenature of past behaviour. Most importantly, an emphasis on the use of the term only on evidence of past dangerous behaviour will permit the concept's use primarily as a <u>descriptive</u> rather than a <u>predictive</u> label (i.e. this individual has committed dangerous acts in the past, which in turn makes it more likely that he will do so in the future) and substantially decrease the likelihood of its use on individuals who have never committed dangerous acts. (p. 220)

Another advantage of using criminal history variables to predict violent criminal behavior is that such criteria match those used by parole boards. Factors most commonly considered in a parole hearing include "commission of serious disciplinary infractions; the nature and pattern of previous convictions; the adjustment to previous probation, parole and incarceration; the facts and circumstances of the offense; (and) the aggravating and mitigating factors surrounding the offense" (Dietz, 1985, p. 32). The closer the match between factors parole board members traditionally consider and the variables in a risk prediction device, the more likely such individuals are to use actuarial predictions in their decision-making.

Research results regarding criminal history can roughly be divided around six factors: (a) number of prior arrests, convictions and incarcerations; (b) severity and nature of past crimes; (c) length of previous sentences; (d) juvenile offenses; (e) street time; and (f) institutional misconduct.

<u>Number of prior arrests, convictions or incarcerations</u>. Included in this category are charges for previous viola-

tions of probation or parole, which have been found to be related to an increased likelihood of continued criminality upon release from prison (Boudouris, 1983; Forst, et al., 1983). One of the most dynamic findings of prediction research is that the probability of commission of a future crime increases considerably with <u>each</u> prior offense. Farrington (1982) noted that the probability of subsequent conviction for violence increased after each conviction for violence, as follows, in a Scottish sample: 14 percent after first conviction; 40 percent after second conviction; 44 percent after third conviction; and 55 percent after four or more convictions for violence. Sanchez (1984), in a follow-up study of previous residents of a juvenile reformatory found that with one prior violent crime the probability of committing a second was .56, with two violent priors the probability of a third subsequent violent crime was .76, with three priors a .71 probability of a fourth, and with four prior violent offenses the probability of committing a fifth was .45. Monahan (1981) reported in a long term study of Philadelphia males that if a person was arrested four times the probability it would happen a fifth was 80 percent. If a person was arrested 10 times, the probability of an eleventh arrest was 90 percent and the probability that the offense would be a serious or "index" offense (although not necessarily a violent one) was 42 percent. Towberman (1984) noted that the major conclusion of the Dangerous Offender Project in Ohio was that an individual with a record of one or more violent offenses will almost certainly commit another offense, and that there is about a 50 percent chance that he will commit another violent offense.

Many studies have used prior arrests, convictions and incarcerations and found them to be among the best predictors of future arrests, convictions and incarcerations (State of Michigan, 1978; von Hirsch & Gottfredson, 1983-84). The majority of studies have found prior convictions to be the most effective predictor (Boudouris, 1983; Dean, 1968; Petersilia, 1985b; Sanchez, 1984; Wainer & Morgan, 1982). Pritchard (1979) in an extensive review of 71 studies found that prior conviction was one of the most stable and robust predictors of recidivism.

Monahan (1978) stressed the importance of using multiple means of verifying the occurrence of offenses, including arrests, convictions and incarcerations, which some researchers have done (Anthony & Oldroyd, 1979; Fischer, 1985; Forst, et al., 1983; Greenwood, 1982; Wentz & Oldroyd, 1979).

At least two studies have used arrests alone very effectively to predict recidivism on parole. Murphy (1980, 1985) instructed coders to carefully read through police "rap" sheets and other arrest records to determine whether or not the evidence indicated that the individual had in fact committed the crime. These subjective determinations were then subjected to tests of interrater reliability. In this manner, the chance of recording a lesser offense (due to plea bargaining, regional disparity in judges, etc.) which commonly occurs when convictions or incarcerations are used as predictors is avoided. At the same time, the chance that an innocent individual is falsely recorded as having committed an offense is minimized.

Regardless of whether prior arrests, convictions or incarcerations are used as the predictor, all except two of the studies reviewed reported statistically (and often meaningfully) significant associations with parole outcome. In one of these studies (Greenwood, 1982) neither prior felony convictions nor prior prison terms were found to be related to self-reported crimes; however, prior arrests and convictions for the same crime as the current offense were both highly correlated with self-reported crimes. It is most likely the difference in criterion (self-reported crime) and the methodological flaws in this study, noted by von Hirsh and Gottfredson (1983-84), which produce results so different from other prediction studies. The other study which reported that neither prior adult arrests nor prior adult convictions were related to success on parole was Anthony & Oldroyd (1979). Interestingly, in a similar study using felony probationers administered the same checklist, both of these variables were found to be significantly related to failure on probation (Wentz & Oldroyd, 1979). In this case, the most likely cause for the observed discrepancy in observed results from most other studies seems to be a difference in the type of offender comprising the study sample (probationers rather than parolees).

In spite of the generally positive findings relative to prior arrests, convictions and incarcerations as predictors of future violence, Monahan (1978) states that based on actual past violence alone, one will be incorrect in predicting future violence (false positives) 19 out of 20 times. Other variables are necessary in order to effectively predict future recidivism or violence.

Severity or nature of past crimes. Sellin and Wolfgang (1964) developed one of the earliest scales to measure offense severity, and most of the studies pertaining to the scale have relied on "public opinion polls" in which respondents are asked to rank crimes according to perceived seriousness. The major problem with the scale is that a great deal of detailed information regarding the offense is required which is not consistently available in file records (specific wounds inflicted on victims, etc.). More recent studies have used categorizations of offenses provided in the Uniform Crime Reports (Federal Bureau of Investigation [FBI], 1972), popular categorizations of "index" crimes from these reports (Kelley, 1976) or simple dichotomies such as person versus property offenses or violent versus nonviolent crimes. Although such simplified systems are certainly not as thorough as the Sellin and Wolfgang scale, the information required from files to complete these more crude indices is at least consistently available.

Many risk assessment systems in current use provide some form of weighting according to offense severity, with more violent past crimes receiving the highest weights (Fischer, 1985; Forst, et al., 1983; Greenwood, 1982; Monahan, 1978). Petersilia (1985b) used a checklist item "serious injury to a victim" in a 40-month follow-up of 1,672 felony probationers. She found that if that item was combined with any two of the following items there was an 80 percent chance of receiving a new prison sentence: (a) conviction on multiple counts; (b) record of at least two prior adult convictions; (c) use of a weapon; or (d) drug involvement.

<u>Length of prison sentences</u>. Generally speaking, the more severe the crime (or crimes) the longer the prison sentence. This is the primary theoretical rationale for inclusion of "length of prison sentence" as a predictor of future recidivism or violent criminal behavior. It has been found to be a reasonably effective predictor in a number of studies despite the confounding influences of plea bargaining, regional disparity in sentencing practices and other complicating factors in the criminal justice system. Forst and his associates (1983) simply used "longest time served, single term" as their measurement of this factor. Greenwood (1982) used a more complex indictor: "Incarcerated more than 50 percent of the two years preceding current arrest." The Greenwood indicator incorporated another commonly used criminal history predictor

known as "street time."

<u>Street time</u>. The proportion of a prescribed period of calendar time (months or years) which an individual remains out of prison or jail is referred to as "street time." There are a number of theoretical rationales for using street time as a predictor: First, if someone has not been committing crimes in the previous 5-year period, he will be unlikely to be arrested, convicted or incarcerated. Out of the previous five years of calendar time, this individual would have five years of street time. In contrast, the more actively criminal individual is more likely to be incarcerated for a portion of the prescribed time and have considerably less street time. The lower the proportion of street time to calendar time, the greater the risk to society.

Street time is a crude measure of the "density" of criminal activity. It can be combined with age to provide another measure of the estimated density of criminal activity by specifying "number of years of street time since 14 years of age," as Fischer (1985) has done. Another option is to weight every prior conviction according to age in street time, as in the case of the 1984 and 1985 versions of the Iowa Risk Assessment Model (State of Iowa, 1985a; 1985c).

<u>Juvenile offenses</u>. The most crude indicators of serious juvenile criminal activity are included both in this review and this study because (a) they are consistently

available in criminal files, and (b) they have been consistently found to be good predictors of future criminality (both violence and property risk). Monahan (1981) summarizes a good number of studies when he states that "research indicates that numerous childhood factors, particularly a history of early violence, relate to the commission of violent behavior as an adult" (p. 92).

One of the most crude indicators of juvenile criminality which has been found to be predictive of adult criminality is the mere presence of a juvenile record (Anthony & Oldroyd, 1979; Monahan, 1978; Wentz & Oldroyd, 1979). More specific indicators which have been found effective are "appearance in court or conviction before 16 years" (Gendreau, Madden & Leipciger, 1980; Greenwood, 1982) and "commitment to a state juvenile correctional facility" (Boudouris, 1983; Greenwood, 1982).

Institutional misconduct. Records of behavior of offenders while incarcerated have been useful in predicting criminal recidivism. Stated as "correctional supervision history" and "supervision risk," these measures have been correlated with parole success .208 and .324, respectively (Anthony & Oldroyd, 1979). In contrast, using the same indicators with felony probationers, neither of these measures had a significant correlation with success on parole (Wentz & Oldroyd, 1979). For murderers, Rans (1982) found that institutional behavior (particularly the absence of segregation) was a good indicator of increased chance of success on parole.

All three of the Michigan studies reviewed found institutional behavior to be particularly effective as a predictor of recidivism (Murphy, 1980; 1985; State of Michigan, 1978). Institutional behavior is therefore included in this study.

Current Offense

Although type of offense for which an individual is currently charged, convicted or incarcerated has not consistently been a good predictor of future criminal violence or recidivism, this variable has been included in the present review because it has been found to be an effective predictor in some recent research, notably studies pertaining to the Iowa Offender Risk Assessment Model. Results of research regarding this variable can roughly be grouped according to the following sub-topics: (a) non-specialization of offense type, (b) high recidivism offenses, and (c) person (or violent) offenses versus property (or nonviolent) offenses. While there are property offenses which are considered violent according to the Uniform Crime Reports (FBI, 1972), most "violent" offenses are crimes against persons.

Non-specialization of offense type. Criminological studies consistently report that it is rare to find individuals whose patterns of criminal behavior are consistently of one type (Monahan, 1981; Peay, 1982). Farrington (1982) found that both official records and self-reports confirm that specialized offenders are rare, although Phillpotts and Lancucki (1979) present evidence that specialization increases with age: For individuals under 21 years, 38.5 percent of violent offenses were followed by violence, whereas for individuals over 21 years, 48.6 percent of violent offenses were followed by violence. Dinitz and Conrad (1978), reporting on the Dangerous Offender Project in Ohio, found that few dangerous offenders are exclusively violent, and when Rotheram and Marston (1982) investigated the relationship between current offense and other measures of aggressiveness (institutional misconduct, etc.) they noted that there were no significant correlations between the two.

Results of factor and cluster analyses also confirm lack of specialization in criminal acts. In one of the most recent and sophisticated studies of this kind, four factors were identified: (a) general crime, (b) traffic offenses, (c) white-collar crime, and (d) sex offenses; and of these, general crime and traffic offenses were found in cluster analyses (Collins, Cliff, Cudeck, McCormick & Zatkin, 1983). These researchers note that a large proportion of crimes in their Danish birth cohort of 28,879 men were shown by both analyses to be independent of any pattern. If one considers only the patterns which were found in both the cluster and factor analyses (general crime and traffic offenses), and excludes most of the traffic offenses (since parolees are generally individuals with histories of considerably more serious crimes and almost all of the men in this cohort are non-criminals), one is left with one factor or cluster: general crime, which again evidences non-specialization of offense type. One study which reported more specialization of offense type than others reviewed was Chaiken and Chaiken (1982a). Twenty percent of their sample reported committing only one type of crime. Since this finding relied on self-reports of criminals, however, there is reason to believe that such factors as selective recall had considerable influence in this case.

High recidivism offenses. One finding that seems consistent in the literature regarding the predictive contribution of current offense type is that some offenses are considerably more likely to be repeated than others and more likely to be indicative of future recidivism. Forst and his associates (1983) noted that federal offenders commit an average of 10 crimes per year of street time and that bank robbers commit an average of 2 1/2 times as many crimes while free as do other offenders. Reports of research in the State of Iowa indicate that offenders convicted of the crimes of robbery, burglary, motor vehicle theft, forgery and writing bad checks show the highest recidivism rates (Fischer, 1983b). Part of the explanation for this phenomenon may be that robbery offenders lead less stable lives than other offenders (Towberman, 1984). Robbers studied in the Dangerous Offender Project were more likely to have prior parole violations, be involved with narcotics, be unmarried and be past escapees from prisons or jails. Also supporting the association between robbery and recidivism, in his careful review of 71 studies Pritchard (1979) found that conviction for auto theft was one of the five most stable recidivism predictors. It should be noted that this was general recidivism which was predicted, and not criminal violence per se. In contrast, Wentz and Oldroyd (1979) found that "current conviction for a high recidivism crime" was not significantly related to recidivism of felony probationers. This difference in findings may be due to a difference in sample populations (probationers versus parolees).

Petersilia (1985b), in a study of 1,672 felony probationers followed up for 40 months, found current conviction on multiple counts was highly related to future recidivism, and reported that regression analyses revealed type of crime (conviction) was one of the charateristics most significantly related to recidivism. Greenwood (1982) found that self-reported charges on multiple counts were not significantly related to recidivism. A major reason why conviction on multiple counts was not found to be significantly related to recidivism in this study may be that since it was robbers and burglars being studied and many of these were charged with burglarizing or robbing several buildings or houses in one area in a single arrest, the types of multiple counts would be considerably different than for other types of offenses. Another reason may be that many of these self-reported multiple counts were later dropped with plea bargaining. More typical multiple counts would be concurrent charges for aggravated assault, robbery and forcible rape, which, it would seem, would constitute a considerably more significant indicator of the future "dangerousness" of an offender on parole.

Fischer (1985) found that current conviction for escape, jailbreak or flight was a significant indicator of future recidivism, particularly violent crime. Dean (1968) noted that whether a crime involved money or not was a significant predictor of parole outcome (phi coefficient of .33); however, he did not specify which type of crime (monetary or non-monetary) was most predictive of future criminality. Not surprisingly, Greenwood (1982) found that prior convictions or arrests for the types of crimes being predicted were useful indicators of future criminality. Since robbery and burglary are two of the "high recidivism" offenses and he was studying exclusively robbers and burglars trying to predict future robberies and burglaries, these findings are understandable. Some of the other more encouraging studies pertaining to type of crime (conviction) have reported a contribution to explained variance (R^2) in recidivism as high as .10 (Petersilia & Honig, 1980).

<u>Person (violent) offenses versus property (nonviolent) offenses</u>. Gottfredson (1967) noted in his review that "offenders against persons have been found at least since 1923 to be generally better risks, so far as parole viola-

tions are concerned, than are offenders against property" (p. 180). Petersilia (1985b) found that property offenders recidivated more quickly and more often. Boudouris (1983), too, reported that persons imprisoned for crimes against property had higher failure rates upon release than persons imprisoned for violent offenses against persons. McCleary (1978) provides a reasonable explanation for this phenomenon: Usually violent offenders are (a) more sure to be convicted and sentenced to prison, and (b) likely to receive much longer sentences than property offenders. After spending a more extended time in prison, such offenders likely try harder to avoid reincarceration.

A considerable number of studies have used the person (violent) versus property (nonviolent) offense dichotomy to considerable effect in predicting future criminal behavior. Dean (1968), differentiating between 97 parole "failures" (offenders sentenced to new prison terms) and 56 parole "successes" (offenders with no legal involvements during first year on parole), reported a phi coefficient of .25 using a violent/nonviolent dichotomy. Forst and his colleagues (1983), in a sample of 1700 federal offenders released in 1970 and followed for five years, also found that recidivism was highly associated with this dichotomy. Sanchez (1984) found that "immediately previous violence" was one of the best predictors of future recidivism. Fischer (1985), using a 4-point scale ranging from the most violent offenses against persons to lesser property and drug-related offenses, reported a Mean Cost Rating (MCR) of .424 for this variable alone. This current offense severity scale resulted in a better single-variable prediction than either prior violence or criminal history scores.

While offenders against persons are generally better risks on parole, they are also more likely to receive prison sentences. This is an important factor to consider when reviewing results of studies which use number and length of prior prison sentences as either predictors or criterion variables. Specifically, Petersilia (1985b) found that if offenders had used a weapon or inflicted serious injuries upon victims they had a higher likelihood of receiving a prison sentence. Fischer and Stageberg (1983) comment on this differential pattern of prison sentencing, as follows:

> Iowa research shows clearly that many of those committed to prison for violent crimes are incarcerated not because of lengthy criminal careers or dangerousness, but due to the severity of a single offense. ...On the other hand, many of the "property offenders" sent to prison constitute real threats to public safety, not only for new property crime, but for violent crime as well. ...Some, while they show only property offenses on their rap sheets, will ultimately "graduate" to armed robbery and other more serious violent offenses. (pp. 23, 24)

While violent offenders tend to be better parole risks, they also tend to have more previous convictions (Farrington, 1982). If offenders are among the few who commit violent offenses _only_, however, they are much less likely to have records of serious crimes as juveniles (31 percent) compared to those committing property offenses _only_

(57 percent) or those committing <u>both</u> property and violent offenses against people (63 percent). Farrington (1982) also reported that those convicted of <u>only</u> violent offenses as adults tended to be older at the time of their first convictions than those of the other two groups.

Cline (1979) found that the United States Uniform Crime Reports (FBI, 1972) showed that peak ages for arrests for violence (24 years) and sexual offenses (26 years) are later than for property offenses such as burglary (17 years) and theft (17 years). One of the implications of this trend is that if young age is used as a predictor, general recidivism (which includes burglary and theft) may be reasonably well predicted. On the other hand, if one depends on youth as a predictor of serious criminal violence, one will greatly overpredict, due to inclusion of many property offenders, among other factors.

<u>Substance Abuse</u>

Research results pertaining to the relationship between substance abuse and criminality can roughly be divided into four subtopics: (a) general substance abuse, (b) alcohol abuse, (c) use of narcotics/opiates/hallucinogens, and (d) use of PCP, non-opiate injections and sniffing of volatile substances.

<u>General substance abuse</u>. Many studies or reports do not specify the nature or even severity of substance abuse. For this reason only generic statements pertaining to the relationship between criminality and substance abuse can be

made from this research. Both the nature and degree of substance abuse, and the strength of relationship between recidivism and substance abuse seem to vary considerably between samples within different geographical areas or different criminal justice programs. While Anthony and Oldroyd (1979) found that substance abuse was not significantly related to success of <u>parolees</u>, Wentz and Oldroyd (1979) noted a statistically significant relationship between substance abuse and success of felony <u>probationers</u>. Boudouris (1983), in a sample of 468 parolees reported that failure rates of substance abusers were higher than other parolees regardless of the extent to which they participated in substance abuse treatment programs. In a Canadian study of 802 offenders, "any current drug offense" predicted reconviction within two years (Gendreau, Madden & Leipciger, 1980). Although this indicator was useful, in combination with other variables, in predicting the highest and lowest risks accurately (77 percent), medium risk classifications were only 42 percent accurate.

Megargee (1982) proposed a number of rationales for the relationship often observed between substance abuse and criminality: (a) crime used to support substance abuse habits, (b) substance abuse reduces inhibitions against aggression or other criminal activity, and (c) substance abuse magnifies the "insufficient stimulus" which seems characteristic of many criminals, thereby increasing stimulus-seeking or criminal behavior. Future research may reveal that one, all, or none of these reasons may actually explain the association between substance abuse and criminality.

Fischer (1985) reports a Mean Cost Rating (accuracy above chance) of .142 for substance abuse as a predictor of violent criminal behavior of parolees. He performed a computer check of associations between various types of substance abuse and recidivism which yielded the following coding: (a) highest risk--history of PCP use, non-opiate injections, or sniffing volatile substances; (b) high risk--history of opiate addiction or heavy hallucinogen use; (c) lower risk--history of other drug or alcohol problem or history of infrequent use of opiates or hallucinogens; and (d) lowest risk--no history as above.

Alcohol. Both Gottfredson (1967) and Pritchard (1979), in their extensive reviews, reported that history of alcohol abuse was among the top five most consistent unfavorable prognostic signs for parole performance. While Ladouceur and Temple (1985) concluded from their review of literature that alcohol was more frequently (than other substances) associated with violent and sex-related crimes, they found in a national sample of 9,142 offenders that violent criminals were only slightly more likely than others to have been using alcohol immediately prior to the offense for which they were convicted. They also found no clear division regarding self-perceived effects of alcohol according to whether current offenses were violent as opposed to nonviolent or sexual as opposed to nonsexual offenses. There was no support for a direct link between alcohol use and crime, since many offenders tended to drink <u>less</u> at the time of the offense than during the previous year.

In an Iowa sample of 468 parolees, Boudouris (1983) found that generally prisoners identified as alcohol abusers had the highest failure rates and their treatment modality did not significantly alter those failure rates. Likewise, in their proposed point scores for selecting career criminals, Forst and his colleagues (1983) gave "heavy use of alcohol" a weight of "+5" since it was found to have one of the highest associations with recidivism. Monahan (1981) in his review listed alcohol abuse as one of the most stable predictors of criminal violence and 60 percent of one of the Rand research samples (Petersilia, Greenwood & Lavin, 1977) said they had committed their crimes under the influence of drugs, alcohol or both. Half of these stated that their intoxicated or drugged condition contributed to the commission of their crimes, although such attribution has been criticized as a form of "deviance disavowal" (Ladouceur & Temple, 1985). Offenders involved with both alcohol and drugs committed more than twice the number of crimes against persons as offenders involved with neither.

Bonham and his colleagues (1984) used one of the more detailed categorizations of alcohol usage of the many studies reviewed, and included alcohol usage as one of the six qualifying secondary variables for entry into a discriminant equation. The values coded for this variable included: (a) no alcohol problem noted, (b) alcohol addiction, (c) habitual excessive drinking, (d) episodic excessive drinking, and (e) no history of episodic excessive drinking but was drinking at the time of involvement in the offense. Although this does not appear to be a rank-ordered categorization, it was found to be reasonably predictive of recidivism.

Narcotics/opiates/hallucinogens. Like alcohol, drug abuse has been found in many studies to be predictive of recidivism on parole. In Pritchard's (1979) review, pre-prison opiate abuse was found to be positively related to criminal recidivism in all nine studies investigating this factor, and Gottfredson (1967) noted that since 1923 drug history, particularly opiate drug use has been consistently useful in identifying subgroups having a higher probability of returning to crime than convicted offenders generally. Greenwood (1982) found that both "drug use in past two years" and "drug use as a juvenile" were significantly related to self-reported crime of burglars and robbers.

When drug involvement was combined with any two of the following list of characteristics, Petersilia (1985b) found that there was an 80 percent probability of a future sentence for re-incarceration in prison: (a) conviction on multiple counts, (b) serious injury to victim, (c) use of a weapon, or (d) record of at least two prior convictions.

Rans (1982) noted that most of the offenders in a sample of 371 murderers released from Illinois institutions (1967 to 1981) had histories of drug abuse and Monahan (1981) in his review of literature listed use of opiates among the top five predictors of criminal violence. In contrast, Sanchez (1984) included drug use among variables investigated but such involvement was not found to be among the best predictors of recidivism.

Regarding the nature of the relationship between crime and drug abuse, specifically narcotics addiction, Speckart (1984/1985) used structural equation modelling (similar to path analysis) to identify causal relationships. Results, in accordance with previous literature, indicated that (a) criminality often precedes narcotics addiction, and (b) criminality shows a strong, positive relationship with levels or rates of narcotics use. Speckart noted that the most reasonable conclusion from available earlier studies and his data was that the great preponderance of crime committed by addicts is engendered by high levels of narcotics use.

While individuals may be motivated to commit crime to obtain money with which to buy drugs, the evidence does not support a direct link between drug use and crime. Ladouceur and Temple (1985) found in interview responses of a sample of 9,142 offenders housed in 215 state correctional facilities that drug use was more often correlated with non-violent property crimes and heroine use particularly with money-making offenses. Since 30 to 50 percent of regular drug users in the sample reported that they did <u>not</u> use them at the time of the offense for which they were currently convicted, intoxication with drugs does not appear to cause crime. Burglars reported the highest use of drugs in all categories and barbituates were linked to crime more often than any drug except alcohol. Amphetamines and cocaine showed no link to violent or sex crimes and marijuana was not found to be associated with any type of crime. Tranquilizers, other sedatives and psychedelics were found to be so infrequent that concerns about relationships with crime were considered unwarranted. Ladouceur and Temple concluded that ultimately substance abuse may contribute to the <u>seriousness</u> rather than the <u>occurrence</u> of crime.

Wainer and Morgan (1982) listed the Salient Factor Score codes for drug history as either "no history of opiate or barbituate usage" or "otherwise," while Forst and his colleagues assigned a point value of "+10" in accordance with results of their research to select career criminals. Bonham, et al. (1984) coded drug history more ambiguously as (a) no drug problem noted, (b) dependency (addiction), (c) periodic excessive drug use, (d) short-term nondependency use, and (e) no history of short-term nondependency use of drugs noted, but inmate was using drugs at the time of involvement in the offense.

<u>PCP/non-opiate injections/sniffing volatile substances</u>. One of the factors in Fisher's (1985) "serious offender"

rating is drug abuse involving the three particular types of drug use which stood out as exceptionally good predictors of serious recidivism and violence:

- History of PCP (phencyclidine) use
- History of non-opiate injections (e.g., amphetamines, barbiturates, cocaine, or any other substance other [sic] than an opiate, injected illicitly)
- History of sniffing of volatile substances (glue, paint thinner, gasoline, etc.). (p. 22)

These drugs were identified as predictors through a manual analysis of 400 cases, in which serious recidivists and violent offenders were compared with other offenders. This is consistent with a ranking of "perceived severity" developed by Stone-Meierhoefer and Hoffman (1982) which rated from least to most severe: amphetamines, hallucinogens, barbiturates, methamphetamines, and phencyclidine (PCP). One problem which Murphy (1985) noted with the most severe, high-risk drug categories (at least for Michigan samples) is that only a very small proportion (approximately 2%) of offenders have histories of using these drugs. With such a small proportion of cases in Fischer's (1985) three highest drug categories, the potential predictive value is minimal at best.

Age-Related Variables

Leading experts in criminology have stated, "there is reason to believe that age could replace social class as the master variable of sociological theories of crime" (Hirschi & Gottfredson, 1983, p. 553). Major reasons these authors give for such support of this variable as a predictor of recidivism include the stability over time (no change in age-crime relationship in 150 years), across cultures (distributions from Argentina, USA, England and Wales are indistinguishable) and invariance across sex and race. Research results regarding age as a predictor of recidivism can roughly be divided into the following subcategories: (a) age at first arrest and conviction or appearance in court before 16 years; (b) age at time of current offense, arrest or conviction; (c) age at time of current release; (d) age and type of crime; and (e) age and criminal history.

Age at first arrest and conviction or appearance in court before 16 years. The age-related variables which have consistently been rated as the best predictors of recidivism are those listed in this subtitle. Wentz and Oldroyd (1979) report a correlation of .404 between age at first arrest and recidivism, Dean (1968) reports a correlation of .39 and Wainer and Morgan (1982) report a correlation of .60. Pritchard (1979) in a review of 71 studies lists age at first arrest as one of the five best and most stable predictors of recidivism. Similarly the checklist item "arrest, conviction or appearance in court before 16 years" has been found to be an extremely good predictor of recidivism (Anthony & Oldroyd, 1979; Greenwood, 1982; Fischer, 1983b). A recent Canadian study found this variable to be the best single predictor of recidivism (Gendreau, et al., 1980). Other studies which have found similar variables to be excellent predictors of adult criminality and recidivism include Farrington (1983), Farrington and West (1981), Robins (1970) and West (1982).

<u>Age at time of current offense, arrest or conviction</u>. Several studies have tried this use of age as a predictor, with mixed results. Anthony and Oldroyd (1979), Gendreau, et al. (1980) and Sanchez (1984) did not find support for this use of age as a predictor, whereas Greenwood (1982) and Wentz and Oldroyd (1979) did report a significant relationship with recidivism. Greenwood used a checklist item "age under 23 at time of arrest."

<u>Age at time of current release</u>. Findings regarding this use of age as a predictor of recidivism have been more consistent and positive than those for age at arrest or admission. Age at release has been found to be negatively related to recidivism on parole. Hirschi and Gottfredson (1983) state, "the empirical fact of a decline in the crime rate with age is beyond dispute" (p. 565). Dean (1968) found that age at release had a correlation of -.43 with parole outcome. Petersilia and Honig (1980) found that age at release contributed only .01 to explained variance (R^2) in a Michigan sample. Bonham, and his colleagues (1984) also found that age at release, by itself, made a very modest contribution to the prediction of recidivism; however, this was likely due to the fact that technical parole violations were included in the criterion. Sanchez (1984) found that one of his better predictors of recidivism was "age under 30" at release.

A parallel phenomenon to high-risk weightings for youthfulness has been the "burn-out" phenomenon (Hoffman & Beck, 1984) whereby offenders over 45 years are rated as the lowest risks for recidivism on parole. This has also been referred to as "maturational reform," "spontaneous remission" and the "aging-out" effect (Hirschi & Gottfredson, 1983, p. 553). These authors have noted that "even with equal exposure to criminal influences, propensity toward crime tends to diminish as one grows older" (p. 566). Gottfredson (1967) in his extensive review of literature from 1923 to 1967 notes that the probability of parole violations consistently decreases with age. Other researchers have noted both the "youthfulness" and "burn-out" effects in their research (Forst, et al., 1983; Hoffman & Beck, 1984; Monahan, 1981).

Age and type of crime. Both Farrington (1982) and Hirschi and Gottfredson (1983) noted that in many studies age for crimes against persons peaks later than for crimes against property; however, Hirschi and Gottfredson reported that self-report data do not support this distinction. Self-reports place the peaks for both person and property offenses at 14 to 16 years, the same peak noted in official records for property offenses. Other studies cited by Hirschi and Gottfredson reported that 15 to 17 year olds had the highest arrest rates for any age group. Sanchez (1984) reported later peak ages for both violent and nonviolent offenses (20 to 24 years). Another phenomenon which Hirschi and Gottfredson (1983) noted was that rates for crimes against persons declined more slowly with age than rates for crimes against property, after their respective peaks.

Godfrey and Schulman (1972) found that age was the best discriminator between groups of offenders with current sentences for (a) crimes against persons, (b) crimes against property and (c) paper-and-pencil crimes. Property offenders were significantly younger (mean age 23) than either person offenders (mean age 29) or paper-and-pencil offenders (mean age 30).

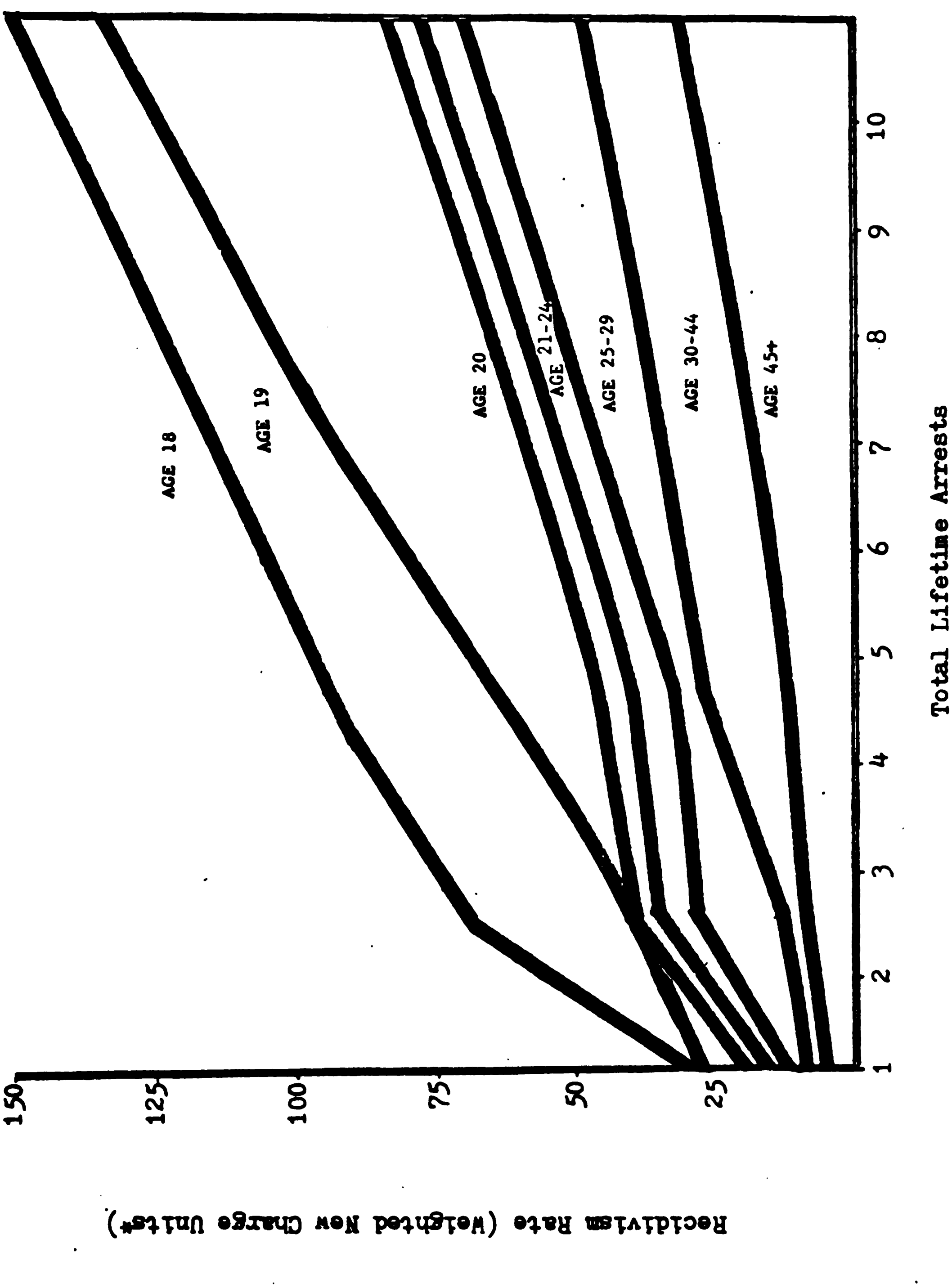
Age and criminal history. Age has been found to be a particularly effective predictor when combined with various criminal history measures. One of the most useful findings regarding the interaction of age and criminal history was summarized by Fischer (1983b) when he stated, "Younger offenders with serious juvenile records tend to pose the highest risk of recidivism, while older offenders with serious adult records tend to be treated the most harshly by judges and parole boards" (p. 4). The age-by-criminal history phenomenon has been delineated by the developers of the Iowa risk models, as may be seen in Figure 2.1. Sánchez (1984) found that after an offender had committed a second violent offense, only age remained as an important predictor of recidivism. Very recent violence was the best predictor, but its impact was modified by age.

Fischer (1985) provides the most complex interactive combination of age and criminal history available for

Figure 2.1. Recidivism rates for convicted offenders in Iowa by age at release and total lifetime arrests.

Note. From _Recidivism Research in Iowa_ by D.R. Fischer, 1980, Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center, p. 14.

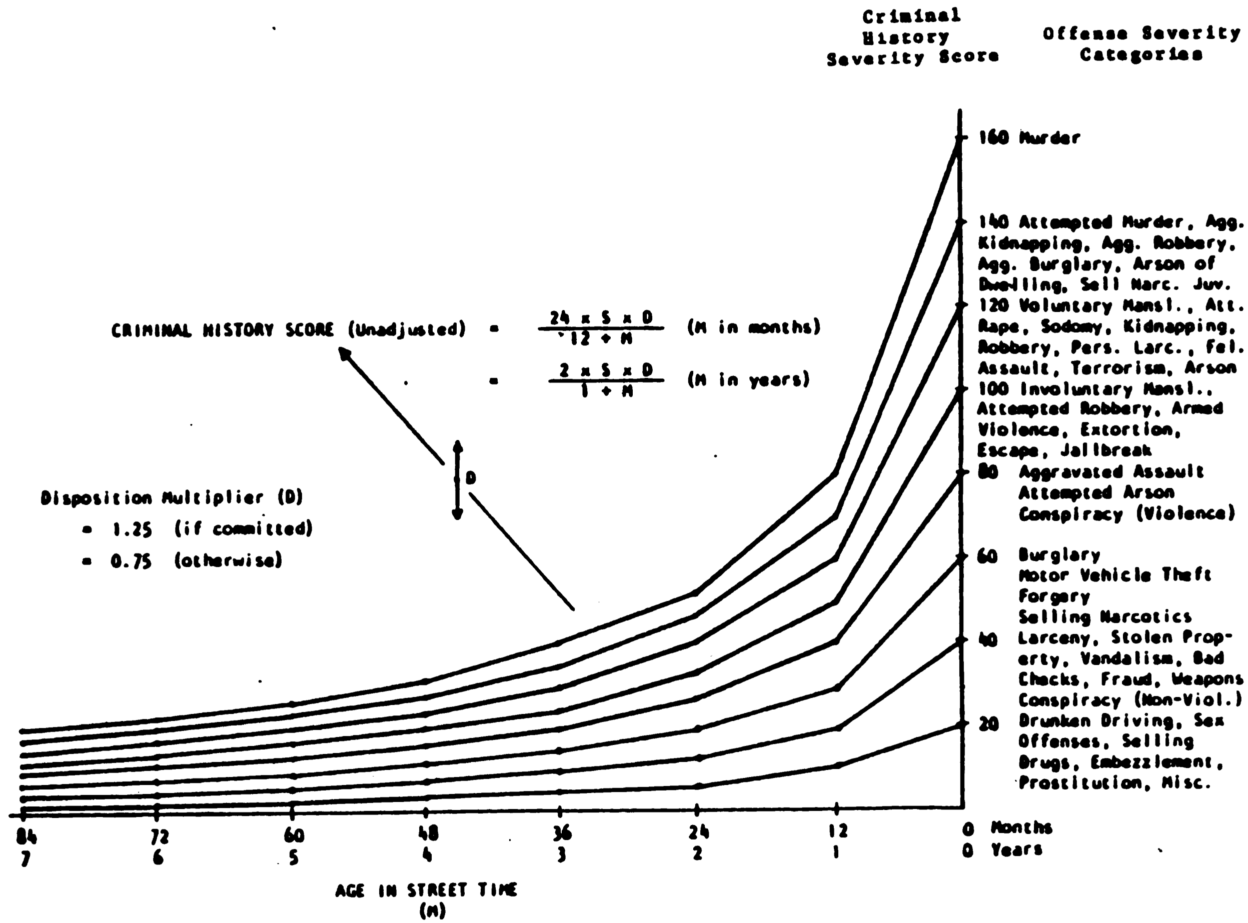
* An arbitrary unit of measurement developed by Daryl Fischer


AGE 18
AGE 19
AGE 20
AGE 21-24
AGE 25-29
AGE 30-44
AGE 45+
150
125
100
75
50
25
1
2
3
4
5
6
7
8
9
10
Total Lifetime Arrests
Recidivism Rate (Weighted New Charge Units*)

predicting recidivism. He weights prior violence score by age in calendar time and offense severity, and weights criminal history score by age in street time and offense severity. (See Figures 2.2 and 2.3) Each bending line as it is traced from left to right in Figures 2.2 and 2.3 represents an increasing predicted risk of felonious recidivism (Criminal History Score in Figure 2.2 and Prior Violence Score in Figure 2.3) for a particular offense severity category. The top line in both figures represents the category which includes murder. In both figures it can be seen that the predicted risk scores (either Criminal History or Prior Violence) which run up the right margins of the figures increase (for each offense severity category) with a reduction in time since the offense. This is particularly so if the offense occurred within two years prior to release on parole. The symbol "D" and vertical line with bidirectional arrows (in Figure 2.2) symbolizes the effect of the disposition multiplier in the computational equation for Criminal History Score: multiplying the score by 1.25 if the conviction resulted in commitment to a correctional institution, and multiplying it by .75 otherwise. Both of these combinations have reportedly provided good predictions. (See Figures 2.2 and 2.3.)

<u>Recidivism (Criterion)</u>

The importance of criterion measures has been attested to by a number of researchers in the field of criminology. Gottfredson (1967) stated, "The need for improvement of



<u>Figure 2.2</u>. Iowa Criminal History Score coding (1984/85 versions).

<u>Note</u>: From <u>Prediction and incapaciation: Issues and answers</u>, by D.R. Fischer, 1985, Des Moines, IA: Statistical Analysis Center, Office for Planning and Programming, p. 21.

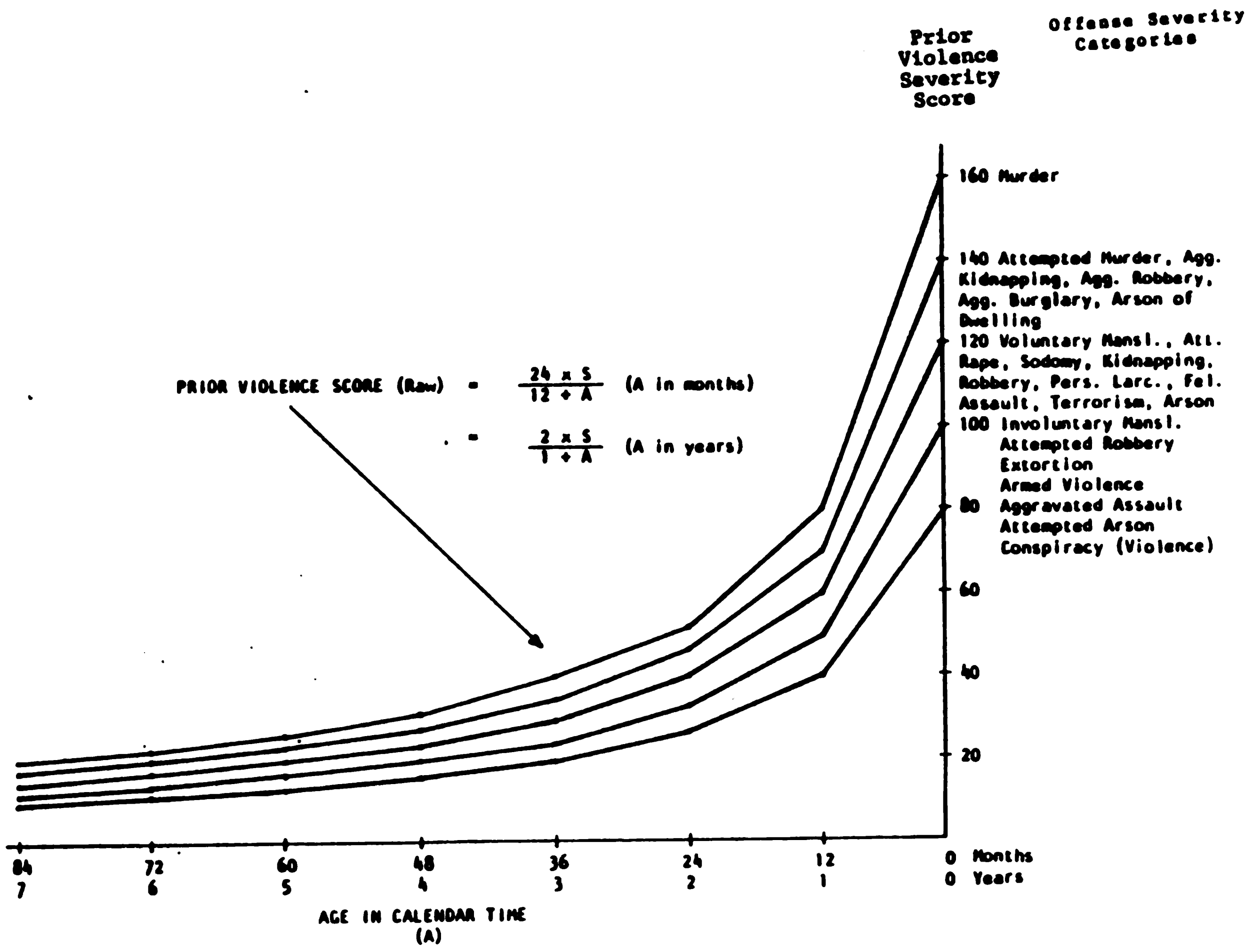


Figure 2.3. Iowa Prior Violence Score coding (1984/85 versions).

Note: From *Prediction and incapacitation: Issues and answers*, by D.R. Fischer, 1985, Des Moines, IA: Statistical Analysis Center, Office for Planning and Programming, p. 20.

reliability and validity of measures of criminal and delinquent behavior is a much neglected field, and it is only beginning to receive careful attention as a measurement problem" (pp. 172-173). Ten years after the Gottfredson article, Gendreau and Leipciger (1978) commented, "Given that the valid measurement of recidivism is so vital it would be expected that the concept itself would have been the subject of a good deal of research. However, the paradox remains that recidivism is one of the least understood and elusive of measures employed in criminal justice research" (p. 3). While one could make the same statement today, a good deal of research as been done, some of which is reported in this section of the paper.

There are a number of ways in which this section could be organized. Monahan (1978) addressed the three issues of (a) definition of recidivism, (b) means of verifying the occurrence of recidivism, and (c) length of follow-up period for determination of recidivism rates. It is also possible to discuss measures of recidivism according to the group of individuals or administrative branches within the criminal justice system from which information regarding recidivism was obtained. The following subsections will constitute a combination of these two means of organizing this information. Subtitles are: (a) definitions and indicators of recidivism, (b) FBI/police records of arrests and convictions, (c) parole records, (d) length of sentence, and (e) length of follow-up.

__Definitions and indicators of recidivism__. A number of definitions and indicators of recidivism have been used and reported in the literature. Each has its own benefits and drawbacks, which is why Monahan (1978) recommends using both multiple definitions, and multiple means of verifying the occurrence of recidivism. The narrowest definition of __violent__ crime in common use includes the four violent "index" crimes from The Uniform Crime Reports (FBI, 1972) which are: (a) murder, (b) forcible rape, (c) robbery, and (d) aggravated assault (Kelley, 1976). Monahan recommends that this definition constitute the high end of a heirarchical ranking of definitions which becomes progressively more inclusive. He suggests that other definitions might include: (a) the above plus "other sex offenses and kidnapping," (b) "all of the above plus robbery, all sex offenses and weapon offenses," and (c) "acts characterized by the application or overt threat of force which is likely to result in injury to people" (Monahan, 1978, pp. 252-253). Megargee (1982) provides a comparable series of definitions and lists all offenses considered violent from NCIC Uniform Offense Codes. Multiple definitions allow for greater comparability across studies and the more inclusive definitions usually permit greater predictive accuracy, since larger targets are easier to hit than smaller ones. To illustrate this increase in predictive accuracy, Monahan (1978) reports that when the four violent index crimes are used as the measure of recidivism, the "true positive" rate is 16 percent; When the definition is expanded to include other sex offenses and kidnapping, the true positive rate is 22.6 percent; When this definition is further expanded to include robbery and all sex offenses, the true positive rate is 53 percent.

Use of the Uniform Crime Reports (FBI, 1972) has been criticized for a number of reasons. A nominal scale of 22 offenses ranging from murder to violation of municipal by-laws constitutes the structure for these reports; however, there is no system to indicate or assess the "quality" or "seriousness" of a crime within any given offense category. Despite such limitations, the widespread acceptance and use of the Uniform Crime Report categories, and the ease of using this system as far as coding offenses, makes this series of definitions a prime candidate for criminological research.

Legal categories, such as those of the Uniform Crime Reports, are often used to approximate criminal behavior and seriousness of the crime. As others have noted, these labels are assumed to represent homogeneous groups of behaviors; however, the confounding of behavior and status in the legal system makes this assumption unwarranted (State of Michigan, 1978). Sellin and Wolfgang (1964) sought to rectify the situation by developing an index which was keyed to behavioral indicators such as the extent and nature of bodily harm to victims, the extent of intimidation or threat and use of weapons. The problem with their scale is that it requires information at a level of detail which is simply not consistently available in administrative files or records in the criminal justice system.

Another measurement concern of considerable importance is the relative proximity of indicators of recidivism to the criminal behaviors they approximate. Since one cannot possibly observe all criminal behavior directly, criminal records must be relied upon. Attributes and influences of the criminal justice system become confounded with criminal acts themselves, until the indicators used to represent criminal behavior distort the original behavior beyond recognition. The problem becomes more severe as one moves further from direct behavioral observations: Reported crimes include the influence of the victims or observers and the police receivers of the reports. Only a certain proportion of reported crimes lead to arrests, and if arrested, the charges are often reduced considerably through plea bargaining and other legal maneuvering. Whether or not an arrested criminal is convicted or sentenced depends upon a good many influences in the criminal justice system, from attitudes of arresting police officers to the policies and practices of parole officers, judges and attorneys involved in each case. Gottfredson and Gottfredson (in press) have noted that correlations between arrests, convictions and sentences are much lower than commonly assumed, suggesting that they are measures of quite different things. This problem has been addressed in criminal justice research reports:

> ...the decision to revoke parole involves a complex interaction of behavior, identification, classification, and legal procedures. In this context, the assumption that "return to prison" is only measuring parolee behavior appears unwarranted...Second, a focus on reconviction or return to prison does not account for the seriousness of the violation. For example, a parolee can be returned to prison for a minor technical violation or for a violent felony, hardly equivalent behaviors. (State of Michigan, 1978, p. 26)

A recent series of studies by the Rand Corporation have used self-reports as indicators of criminal behavior (Chaiken & Chaiken, 1982a; 1982b; Greenwood, 1982), in an attempt to overcome the confusion and confounding relative to legal categories and labels. This use of self-report data has been soundly criticized by von Hirsch and Gottfredson (1983-84). The point is made that there is little opportunity to corroborate the self-reports of crime commission, particularly those of the (self-reported) most highly active criminals, since only a small proportion of the self-reported criminal acts are documented in official criminal records of any kind. The same fault is present in much of the data reported by Sanchez (1984). One can detect a note of sarcasm in the criticism by von Hirsch and Gottfredson as they state, "It seems to be assumed that these individuals are happy to wreak the worst mayhem, but know that lying is a sin" (p. 19). Monahan's (1978) answer to this dilemma is to recommend that <u>multiple</u> means of verifying the occurrence of violent behavior be used in any given study, including: (a) conviction rates; (b) conviction and arrest rates; (c) convictions, arrests and civil commitments to mental health institutions; and (d) all of the above, plus self-reports.

Although some researchers in criminology eschew the use of arrests as an index of recidivism, asserting that innocent people are arrested and then later acquitted, it is this author's contention that they can be one of the most effective indices of recidivism available from official records. If (a) coders are instructed to read carefully over police arrest reports and parole agent file descriptions to determine whether or not sufficient evidence exists to indicate whether or not individuals probably committed the crimes for which they were arrested, and (b) these determinations are checked for intercoder reliability, arrests constitute an extremely good measure of recidivism. It was this procedure which was followed when arrests were used in a series of studies in Michigan (Murphy, 1980; 1985; State of Michigan, 1978).

FBI/police records of arrests and convictions. The most common sources of information regarding recidivism of parolees are FBI and police reports (Reed and Amos, 1972; Sanchez, 1984) and the most commonly used research measure from these sources is reconviction (Gendreau, et al., 1980). As with most official records, these measures have their limitations, as noted by Farrington (1982):

> One of the major problems is that officially recorded violent offenses are the tip of the iceberg of violent crimes committed...
> ...only 10% of rapes, 10% of assaults and 21% of armed robberies committed by their sample of male prisoners led to arrests. (p. 193)

Farrington continues, noting that "records are often incomplete, with an unsystematic coverage of topics of interest, and are usually compiled for administrative rather than research purposes" (p. 194). The statistics which Monahan (1978) reports, although more encouraging than Farrington's, serve to further illustrate the limitations of police records. He notes that only 40 to 50 percent of all violent crime is reported to police (only 27 to 39 percent of simple assaults). In addition, he lists the "clearance rates" (percentage of reported crime resulting in alleged offenders being charged and taken into custody) of various crimes as: (a) 79 percent for murder, (b) 51 percent for forcible rape, (c) 63 percent for aggravated assault, and (d) 27 percent for robbery.

Daryl Fischer (State of Iowa, 1985c) used a total of 14 different criterion measures (see Table 2.1), most of which used FBI or police records, supplemented by parole reports. This seems to be a reasonable approach, since comparisons of results using these different measures could give researchers a reasonably good estimation and understanding of patterns of criminal behavior as it is juxtaposed with various aspects of the criminal justice system.

Parole records. Smith and Berlin (1979) listed three types ~~of parole~~ violations: (a) technical violations (failing to report to parole officer, possibly participating in domestic violence or personal drug use, etc.); (b) absconding (leaving area without notifying parole officer);

Table 2.1. Recidivism Criteria from recent Iowa Studies.

CRITERION I	= Post-release violence = New charge for violent felony
CRITERION II	= New prison sentence for safety crime including violent crimes, weapons crimes, and drug crimes (felonies only)
CRITERION III	= Criterion I or Criterion II = New charge for violent felony _or_ new prison sentence for safety crime
CRITERION IV	= Rearrested
CRITERION V	= Rearrested _or_ returned to prison (as parole violator or with new sentence)
CRITERION VI	= New felony charge
CRITERION VII	= New felony conviction
CRITERION VIII	= Return to prison (as parole violator or with new sentence)
CRITERION IX	= New prison sentence
CRITERION X	= Criterion I _or_ Criterion VIII = New charge for violent felony _or_ new prison sentence
CRITERION XI	= Criterion 1 or Criterion IX = New charge for violent felony _or_ new prison sentence
CRITERION XII	= Institutional violence and serious misconduct = 42+ days lost on the sentence
CRITERION XIII	= Criterion I _or_ Criterion XII = New charge for violent felony (after release) _or_ institutional violence or serious misconduct (before release)
CRITERION XIV	= Days lost on the sentence for misconduct (before released)

Note: From _A comparative study of the predictive validity of classification instruments_ by State of Iowa, 1984, San Antonio, TX: Paper presented at the 114th Congress of Corrections, American Correctional Association, p. 10.

and (c) re-arrest (for serious violations). Often researchers have used a "success/failure" dichotomy as their criterion measure (Bonham, et al., 1984; Dean, 1968; Simon, 1971). This practice has been criticized severely:

> ...[The] designation as a "parole violator" is made on the basis not only of the parolee's behavior, but also on the response of the parole agent or the paroling authority... In this situation, an increase in "parole violations" may reflect increased offending behavior by parolees, increased surveillance by parole agents, or changes in policy of the paroling authority. (Gottfredson, 1967, p. 173)

Levels of parole surveillance intensity vary considerably between offenders, as McCleary (1978) notes:

> The few dangerous men are watched closely and returned to prison at the first opportunity. ...The PO sees his dangerous men and clients nearly every week. He sees his paper men only one or two times a year "...I see most of my men two or three times a year. But they're still <u>on paper</u>." (pp. 126-127)

This comment serves to highlight the confounding effect of parole officer behavior upon records of parolee behavior. Wainer and Morgan (1982) tested out a number of other criterion measures for recidivism on parole and found that "months under supervision" and "months to date of arrest" were the most effective criteria. A recidivism measure developed and used in Michigan (Murphy, 1980; 1985; State of Michigan, 1978) also appears to have a good deal of merit. It is an ordinal measure of parole outcome which, while improving on the dichotomous "success/failure" measure commonly used, does not require the detailed information demanded for the Sellin and Wolfgang (1964) index. The categories are as follows: (a) no behavioral problems, (b) absconded or technical violation, (c) misdemeanor, (d) nonviolent felony, and (e) violent felony.

Length of sentence. The two recidivism measures which have heavily incorporated length of sentence are the Moberg and Ericson (1972) Recidivism Outcome Index and the Canadian Recidivism Index (Cormier, 1981; Gendreau and Leipciger, 1978), which is a Canadian modification of the Moberg and Ericson index. These measures rank recidivism according to the severity of the penalty imposed (whether convicted, what level of offense conviction, length of sentence, etc.). These indices do not attempt to separate legal status and behavior and have been soundly criticized for this characteristic:

> ... For example, "(1) reimprisoned for a new felony" is distinct from "(5) absconder wanted for a new felony" although the behavior measured in the two categories can be identical. If the index were collapsed into a success/failure dichotomy with return to prison as the outcome measured, a parolee returned to prison would be a failure while a parolee who absconded and was wanted for a new felony would be a success even if both had committed the same crime. Therefore, the results of a study using this index would be difficult to interpret. (State of Michigan, 1978, p. 27)

Length of follow-up. There is almost unanimous agreement between researchers regarding the length of follow-up required to adequately measure recidivism. Most authors give two years as the follow-up period required to include both the peak and the majority of offenses committed by parolees (Cormier, 1981; Gendreau, et al., 1980; Moberg and Ericson, 1972; Monahan, 1981). Forst, et al. (1983), in a five-year follow-up study of 1700 offenders, reported that 71 percent of those who recidivated did so within two years of their release. Gendreau and Leipciger (1978) state that "recidivism studies invariably report that, of those who recidivate, the majority do so within the first two years" (p. 10).

There have been studies which have used lesser and greater numbers of months of follow-up, but as Monahan (1978) has observed, the studies using follow-ups of less than two years have resulted in far higher false positive rates. Beyond two years one experiences diminishing returns, although some well-funded studies have completed 40-month follow-ups (Petersilia, 1985a; 1985b). In her sample of 1,672 federal probationers, Petersilia noted that 65 percent were rearrested, 51 percent were reconvicted and 34 percent were sentenced to jail or prison during the 40-month follow-up period.

In order to increase the ease of comparability between studies and permit differential predictions according to the length of time behavior is being predicted, Monahan (1978) recommends the use of multiple time periods for follow-up. He also noted that the longer the follow-up period, the higher the ratio of true to false positives, due to the resultant increase in base rates.

Variables Excluded From Explicit Investigation

This section includes reviews of literature pertaining to (a) psychological tests; (b) childhood and family variables; and (c) employment stability as predictors of criminal recidivism. Because this section considers variables that are not explicitly included in the study these reviews are brief.

Psychological Tests

Gottfredson (1967) listed a number of psychometric predictors of recidivism, including: (a) the Social Adjustment Guide; (b) the Minnesota Multiphasic Personality Inventory--MMPI [particularly the Psychopathic Deviate (Pd) and Mania (Ma) scales]; (c) The California Psychological Inventory--CPI (particularly the delinquency potential scale); (d) The Porteus Maze; and (e) the Rorschach. Although he was not particularly encouraging about the potential of psychological tests by themselves, Gottfredson felt that the combination of results of psychometric assessments and life history information had considerable potential. Since that time, social history information has been shown to be far more useful and efficient in predicting recidivism than psychometric predictors, and the combination of psychological test results with social history information (criminal history, age, current offense, substance abuse history) results in greater shrinkage of predictive accuracy with cross-validation than when social history information alone is used (Gendreau, et al., 1980;

Sanchez, 1984).

One common misconception regarding prediction of violence is that those who are not "mentally healthy" are more likely to commit violent crimes. In fact, the most relevant noncorrelate of violence is "mental illness" (Monahan, 1981). This may be one reason (in addition to poor estimated reliability for the instruments) why psychological tests have not been effective in predicting violent behavior. Of the psychological tests which have been used to predict recidivism, the MMPI is by far the most researched and the most highly regarded. The MMPI is the most widely used personality test in American criminal justice settings today (Gearing, 1979); however, Spellacy's (1978) study is one of very few which have successfully used the MMPI to discriminate between violent and non-violent criminal offenders.

Gearing (1979) reviewed and critiqued 71 investigations of the MMPI relative to criminals and, although he did not find results generally encouraging he did indicate encouraging results for Megargee's MMPI-based typology of criminals (Megargee, 1977; Megargee & Bohn, 1977; and Megargee & Dorhout, 1977; and Meyer & Megargee, 1977). Although a number of studies have cross-validated the existence of Megargee's ten criminal types and several of the behavior patterns attributed to them by Megargee (Booth, 1980; Edinger, 1979; and Edinger, Reuterfors & Logue, 1982), the reliability of the typology has been seriously questioned (Blackmon, 1982/1983).

In the last two years three more studies have attested to the unreliability of the Megargee typology and its inability to predict recidivism or even differentiate between inmates with extensive histories of violent behavior and those without (Johnson, Simmons & Gordon, 1983; Louscher, Hosford & Moss, 1983; Moss, Johnson & Hosford, 1983). If this is not discouraging enough, one can consider the finding that criminals can fake good and bad adjustment on the MMPI very effectively, often without being detected on the "Lie" scale, thereby invalidating the results (Gendreau, Irvine & Knight, 1973; Rice, Arnold & Tate, 1983).

Criminology experts summarize the situation regarding psychometric prediction:

> ...it is cost ineffective, as well as predictively inaccurate to have a core of the risk prediction instrument be variables that measure clinical pathology. (Rans, 1984, p. 10)

> ...Thus, it would appear that this (Megargee) classification system is incapable of providing useful predictive information...Perhaps the focus of these attentions should be diverted away from systems that use psychological data as their focus, such as is the case with the apparently ineffective Megargee typologies. (Moss, Johnson & Hosford, 1984, pp. 231-232)

<u>Childhood and Family Variables</u>

A good number of variables pertaining to childhood, youth and family background have been found to be predictive of both juvenile delinquency and adult criminality. Some of the most important and stable predictors are discussed briefly in this subsection.

Criminality of father. Goodwin and Guze (1984) noted that several follow-up studies of children of criminals indicate that these children, when adopted early in life by non-relatives, are more likely to reveal criminal behavior as adults than are adopted children whose biological parents were not criminals. Mednick, Gabrielli and Hutchings (1983) completed a series of studies testing the influence of heredity upon later criminality, using a longitudinal cohort of 14,247 non-familial adoptions (not randomly assigned) in Denmark. Court conviction was the criteria for criminality. First, they found that biological fathers and male adoptees both had higher mean rates of conviction than adoptive fathers (whose rates were 8 percent below that of the general population). Criminal adoptive parents were found to have a statistically nonsignificant effect upon conviction rates of their male adoptees, whereas the association between biological parent conviction and biological son conviction was highly significant. Further, the more chronic an offender the biological father was, the more chronic the son was found to be, in terms of numbers of convictions.

Other studies supporting the importance of paternal criminality as a salient predictor variable for criminality in male offspring include: Farrington (1978); Farrington, Berkowitz and West (1982); Goodwin and Guze (1984); Knight, Prentky, Schneider and Rosenberg (1983); Lewis, Shanok, Grant and Ritvo (1983); McCord (1983); Mednick, Gabrielli and Hutchings (1983); and Regier and Allen (1983).

Paternal alcoholism. Studies documenting the salience of paternal alcoholism as a predictor of criminality in male offspring include: Goodwin and Guze (1984); Knight, et al. (1983); Lewis, et al. (1983); and McCord (1983).

Raised by mother alone or mother and stepfather together. Studies indicating higher rates of criminality among males raised by mothers alone or mothers and step-fathers together (as opposed to those raised by either the original mother and father together or the mother and either her sister or mother), include: Ensminger, Kellam and Barnett (1983); and Lewis, et al. (1983).

Harsh or inconsistent parental discipline. Studies which have indicated this factor as a predictor of violent criminality and recidivism as an adult include: Farrington (1978), Farrington, et al. (1982), Knight, et al. (1983), Loeber (1982), McCord (1983) and Martin and Guze (1983). There are a good many other variables which have been found to predict criminality in general, but not specifically recidivism or violent crime.

Employment Stability

Employment stability has been reported frequently in the literature as a reasonably good predictor of criminal recidivism. There have been a number of measures of employment stability noted in the literature. Dean (1968) used "percentage of time employed during parole period" and "length of time worked on first release job." He found these measures correlated .23 and .20, respectively, with parole outcome. Greenwood (1982) found that the checklist items "employed less than 50 percent of previous two years" and "more than three jobs in preceding two years" were reasonably good predictors of recidivism, while Gendreau, et al. (1980) found that the checklist item "never held a job over two years" was not a good predictor of recidivism. Rans (1982) found that for murderers, in contrast to other types of offenders, degree of employment stability was not a good predictor of reincarceration.

Preconfinement work record was positively related to success on parole in studies by Anthony and Oldroyd (1979) and Wentz and Oldroyd (1979). Pritchard (1979) found that in 72 of the 76 studies reporting data on the stability of pre-prison employment a lack of stability was found to indicate failure on parole. This was also an indicator for Wainer and Morgan, (1982). Monahan (1981) reports that in a recent Massachusetts study, 89 percent of parolees who had a satisfactory job at the end of their first year on parole completed parole successfully, while only 50 percent of those not satisfactorily employed did so. He further notes, "the probability of recidivism during the second three months on parole increased directly with the number of jobs held during the first 3 months, from 11 percent recidivism when one job was held to 43 percent recidivism when five jobs were held" (p. 110). In addition, Monahan noted that in the Rand study, only 43 percent of the habitual offenders had a minimally acceptable job while on the street as an adult.

Fischer (1985) comments that it has often been judged necessary to include "soft" information such as employment history in risk assessment instruments, but notes that these tend to violate "just desserts" principles. He presents data which indicate that high levels of predictive accuracy can (and should) be established and maintained without such "soft" variables. Hoffman (1983), likewise, has revised the federal Salient Factor Score (SFS'81) excluding employment history as a predictor, with no reduction in accuracy. He explains his desire to eliminate "employment" from the Score, as follows:

> "Employment" proved to be a difficult item to score reliably. In some cases, probation officers did not have time to verify this item before the presentence investigation was due, companies had gone out of business, or an offender had claimed to have worked as a day laborer or "off the books," making reliable assessment difficult. (Hoffman, 1983, p. 543)

Chapter Summary

Numbers of prior arrests, convictions and incarcerations; severity and nature of past crimes; length of previous sentences; proportion of street time to calendar time; indicators of serious juvenile criminality; and institutional misconduct have all been found to be consistently good predictors of criminal behavior on parole. Aspects of criminal history which could be improved or used more effectively include cumulative weightings for past crimes and weighting techniques for severity of offenses. To date, the recent versions (1984, 1985) of the Iowa risk model provide the most complex indices of street time and these instruments have contributed a good deal regarding cumulative weightings for past crimes. A number of studies in Michigan have found institutional misconduct to be an effective, reliable predictor.

Due to non-specialization of crime types and better risk potential of many individuals with current violent offenses against persons, the use of current offense against persons (violent) would not seem to be a particularly good predictor of future criminal violence (although Fischer, 1985; Forst, et al., 1983; and Petersilia, 1985b have reported that type of current offense is highly related to future criminal behavior). While robbery, burglary and auto theft have been found to be among the most "high recidivism" offenses, these are primarily predictive of each other (or lesser property offenses) rather than the most serious violent offenses (homicide, forcible rape, aggravated assault and kidnapping). Current convictions on multiple counts seem to be predictive of both general and violent recidivism to some extent.

Substance abuse (particularly alcohol and heroin) has been consistently found to be a moderately useful variable for predicting criminal recidivism; however, due to the small proportion of cases with histories involving the drugs found to be _most_ predictive of criminal violence (such as PCP and sniffing volatile substances), such indicators are of questionable significance.

Age at first arrest, age at time of current release and age combined with criminal history have all been found to be very effective predictors of both recidivism in general and criminal violence. In contrast, the findings regarding age at time of current offense and age combined with type of crime have been equivocal at best.

If arrest records are coded carefully and checked for reliability (particularly if they are documented from multiple sources) they constitute good measures of recidivism. Generally speaking, ordinal rankings are preferred to success/failure dichotomies as measures of recidivism. One of these ordinal scales which is appropriate for the level of detail and consistency available in most criminal justice files was developed in Michigan (Murphy, 1980; 1985; State of Michigan, 1978). Recidivism indices most accurately reflect behaviors they represent when they are confounded the _least_ with legal categories. The Michigan index provides a promising measure in this regard as well. The minimum follow-up period recommended for measurement of recidivism is two years. The most recent Michigan sample (Murphy, 1985) exceeds this length of follow-up.

Monahan (1981), after reviewing a considerable amount of literature relative to the use of psychological tests to predict violent behavior, supports the conclusion that "no test has been developed which will adequately postdict, let alone predict, violent behavior" (p. 80). For these reasons psychological tests are excluded as variables for this study.

Although there have been many more variables found to be predictive of criminality, including: criminality of father, paternal alcoholism, mother only or mother-stepfather parenting, harsh or inconsistent parental discipline, physical and sexual abuse as children, disruptive and violent family life, involvement with delinquent peer gangs and rejection by parents, such "soft" variables are difficult to clearly identify and quantify with any reliability.

The major reason none of these variables has been included in this study (though some studies have demonstrated reasonably strong relationships with recidivism) is that the information required to code such variables reliably and validly is not consistently available in criminal files. To perform the longitudinal observations and interviews necessary to research many of these variables would take a great deal more time and money than is available for this project.

Employment stability, although found to be a reasonably good predictor of criminal recidivism in some studies, has also been effectively excluded from instruments which previously included this variable, with no loss in overall predictive accuracy. In addition, it has been found to be particularly difficult to reliably measure. For these reasons, employment stability was not among the variables included in this study.

CHAPTER III

Review of Literature:

Methodological and Statistical Developments

In chapter one the need for, use of, and alternatives to, prediction were discussed briefly. This chapter will address (a) the extent to which prediction of recidivism and violent criminal behavior may be possible, (b) the limitations upon such predictions, (c) tests of predictive accuracy, and (d) methods of combining predictor variables.

The Possibility of Prediction

One of the most encouraging findings pertaining to criminal recidivism has been that a "hard core" minority of offenders is responsible for a large portion of crime committed (Farrington, et al., 1982; Loeber & Dishion, 1983; Magnussen, Stattin & Duner, 1983; Wolfgang, 1983). To counter this, one of the most discouraging findings has been the proportion of "false positives" (predicted recidivists who do not commit future reported crimes) to "true positives" (accurate predictions of recidivism). Results regarding actuarial (often referred to as "statistical") prediction have been considerably more encouraging than those relative to clinical prediction. These and other related issues will be discussed briefly in this section of the chapter.

Hard core recidivists. Elliott and Huizinga (1984) report that 8.6 percent of their national sample of 15-21 year old respondents committed 80 percent of all serious (index) crimes and over half of all crimes reported by cohort members. In addition to the references cited earlier, this phenomenon of a small group of recidivists committing a large proportion of crime has been noted by Greenwood (1982), Chaiken and Chaiken (1982a; 1982b) and Fischer (1985). Forst and his colleagues (1983) identified 200 from their sample of 1700 federal offenders (12 percent) who committed approximately 10 times as many non-drug crimes per year as the other 1500 offenders. During the 5-year follow-up period, 85 percent of the 200 were rearrested while only 36 percent of the other 1500 offenders studied were rearrested. Also, although outnumbered 7.5 to 1, the group of 200 committed an estimated 1900 more crimes per year than the remaining 1500. Farrington (1982), in his review of 27 longitudinal studies of criminals, noted that in one study (not an uncommon example) 6 percent of the offenders studied committed (a) 71 percent of the homicides, (b) 73 percent of the rapes, (c) 70 percent of the robberies, and (d) 69 percent of the aggravated assaults reported for the sample. It would seem that the existence of such a stable, hard core group of recidivists would facilitate identification (prediction) of offenders who would commit serious crimes while on parole.

False positives. Sadly, however, the ratio of false to true positive predictions remains high (Wilkins, 1980). Figure 3.1 is an illustration of the relationship between false positive predictions and other outcomes. In the Forst et al. (1983) study false positives outnumbered true positives by nearly 6 to 1. Monahan (1981) reported the identification of a small class of less than 3 percent of offenders, of whom 14 percent were expected to be violent, but 86 percent of those identified as potentially violent were not, in fact, discovered to have committed a violent act while on parole. Further, Monahan (1981) notes that the <u>best</u> predictions of criminal violence have achieved a 3 to 1 (false to true positive) prediction ratio. Sanchez (1984) reported a 4 to 1 ratio. Wainer and Morgan (1982), using their latent trait estimators achieved among the highest accuracy rates, ranging from 39 percent to 47 percent true positives. The effect of "false positive" and "false negative" predictions upon the people they affect was summarized by Monahan (1978):

> It is a rare prisoner who will accept with equanimity the explanation that he must be denied parole because the odds are one-in-three that he will be violent upon release. It is an even rarer victim of violent crime who will care to listen to a treatise on the difficulty of predicting low-base-rate events. (pp. 265-266)

In light of this high proportion of false positive predictions, Farrington (1982) cites four major authors in criminology who have concluded that "dangerousness" can <u>not</u> be predicted. He summarizes results of a great deal of

	Predicted Arrest for Violent Felony	
Observed Arrest for Violent Felony	Yes	No
Yes	"True Positives"	"False Negatives"
No	"False Positives"	"True Negatives"

Figure 3.1. A 2x2 matrix of predicted by observed arrests for violent felonies.

research, stating, "On the criterion of a statistically predictive relationship, convictions for criminal violence can be predicted. On the criterion of a low false-positive rate, they cannot" (Farrington, 1982, p. 189). The major factor limiting predictive accuracy is the base rate. This is discussed in a later subsection of this chapter, along with other limiting influences. Von Hirsch and Gottfredson (1983-1984) noted that one of the alternatives to high proportions of false positives would be to shift cutting scores, but they also noted that to do so would result in trade-offs with increases in false negative predictions.

Monahan (1981) has observed that the establishment of cutting scores in making predictions is much more a political than an empirical question, and Farrington (1982) notes that it is important to consider the rates and social costs of false negatives as well as false positives. Other researchers have attested to the appropriateness and importance of differential weightings (assignment of values) to outcomes of predictions (Gottfredson, 1967; Loeber & Dishion, 1983; Monahan, 1981; Wainer & Morgan, 1982). Regarding differential weighting of prediction outcomes, Monahan (1981) has stated the following:

> Overall accuracy is _not_ the only factor involved in prediction. One may wish to _weigh_ different kinds of errors differently. Thus, in mental health law (e.g., civil commitment), it appears legally acceptable to weigh a false negative (e.g., a released patient who injures someone) more heavily than a false positive (e.g., a safe person erroneously hospitalized as dangerous). (p. 60)

Loeber and Dishion (1983) have proposed a number of specific options and techniques for differentially weighting the consequences of decision alternatives. The following brief table illustrates utility values assumed for the total percent correct index, compared with two alternative utility estimation policies:

Table 3.1. Differential weighting of prediction outcomes.

		Total Percent Correct	Policy 1	Policy 2
	Valid Positives = U_1	+1	+1	+1
Prediction	False Positives = U_2	0	0	-1
Strategy	False Negatives = U_3	0	-1	0
	Valid Negatives = U_4	+1	+1	+1

Note. From "Early predictors of male delinquency: A review" by R. Loeber and T. Dishion, 1983, Psychological Bulletin, 94, p. 96. Copyright 1982 by the American Psychological Association, Inc.

Clinical vs. actuarial ("statistical") prediction. One of the most consistent findings of research involving prediction of recidivism has been that actuarial predictions are more accurate than clinical predictions (American Psychological Association, 1978; Fischer, 1985; Forst, et al., 1983; Gottfredson, 1967; Gough, 1962; Meehl, 1954; Rotheram & Marston, 1982; Wilkins, 1980). Based on this research, Monahan (1981) has concluded, "Indeed, so many studies have reached this conclusion that 'actuarial prediction is better than clinical prediction' has become a truism in psychology" (p. 97). Wormith and Goldstone (1984) have further demonstrated that when clinical prediction is incorporated in statistical (actuarial) prediction schemes, the resulting predictions prove less accurate on cross-validation than actuarial predictions without these additions.

In spite of the fact that actuarial techniques have demonstrably greater accuracy than clinical techniques, they have their limitations, as expressed by Gottfredson, Wilkins and Hoffman (1978):

> Using an actuarial parole aid is a little like using a weather report that says there will be a 60 percent chance of rain. What the weather report actually means is that on similar days it rained 60 percent of the time. It does not tell whether or not it will actually rain today. Nevertheless, such information can be useful in deciding whether or not to carry an umbrella. (p. 54)

Monahan (1984) encourages future researchers to explore actuarial prediction techniques, when he states:

> Other forms of prediction, emphasizing actuarial methods...have been largely unexplored. Yet it is precisely these other forms of...prediction that are the most promising candidates for a workable level of predictive accuracy. The absence of evidence that violence can be validly predicted in some situations should not be construed as evidence of the absence of such validity. (p. 11)

In light of these recommendations and results of related research, the present study is actuarial in nature.

The Limitations of Prediction

Major limitations upon the accuracy of recidivism predictions include: (a) the quality of criminal justice data, (b) the base rate of the event or criterion being predicted, and (c) the selection ratio. Each of these limitations is discussed briefly in this subsection.

Quality of data. Commenting on criminal justice data, Zwanenburg (1977) stated, "Even the most sophisticated analytic methods cannot transcend the quality of the data available and it has become abundantly clear that the data are of rather poor quality" (p. 40). Cautions have also been expressed by other researchers regarding the reliability and validity of both predictor and criterion variables extracted from criminal justice files (Gottfredson, 1967; Loeber & Dishion, 1983; Sanchez, 1984; Wainer & Morgan, 1982; Wilkins, 1980). Concerns center around measures which do not distinguish between actual behavior and legal categories. Other criticisms include the "static" rather than dynamic character of many predictor variables and the "empirical" rather than rational selection of predictors.

Dean (1968) criticized most common predictor variables for failing to account for variations in parolees' release circumstances and for being completely extrinsic to the individuals involved. The failure to account for parole release circumstances was also noted by more recent researchers (Monahan, 1978; State of Michigan, 1978). Monahan proposed elaborate environmental assessments which incorporated behavioral contingencies affecting offenders; however, when Edinger (1977/1978) incorporated such measures in a complex design, the inclusion of these assessments did not improve upon actuarial predictions alone, when subjected to cross-validation.

Astone (1981) attempted to develop measures of factors contributing to recidivism on parole which were more intrinsically related to the parolees involved. He obtained both parolee and parole officer perceptions of the most important factors contributing to failure (recidivism) on parole. Beginning with a list of 5,004 responses, he settled on a list of 151 items, each listing reasons why parolees returned to prison. These were divided into 13 categories, using a variety of psychometric analyses, and final questionnaires were administered to 54 parole violators and 50 parole officers. While the parole violators attributed their failures to various aspects of imprisonment, parole supervision, police, courts, employment, society and family and friends, the parole officers most often listed lack of self-control, poor personal attitude and lack of employment persistence of parolees as the most important contributors to their recidivism.

A number of criminology experts have criticized the approaches to selection of predictors as one of the important weaknesses of current research. Approaches to the construction of psychological or behavioral assessment instruments can roughly be divided into three types: (a) empirically derived or criterion-related; (b) rationally derived or content-related; and (c) factorially derived or construct-related (Aiken, 1979; Thorndike & Hagen, 1961). Purely empirical test construction is a procedure which is nontheoretical or atheoretical in nature and involves primarily statistically-derived relationships between an instrument or predictor and one or more external criteria. Purely rational test construction is theoretically-based and involves construction based on logic rather than empirical testing. Monahan (1978), Nunnally (1978) and Travers (1951) all eschew purely empirical test construction primarily for the lack of contribution which such research makes to the development and testing of theory. Dean (1968) also stresses the need to relate parole prediction to theories of criminality and suggests a number of theoretically relevant variables. Further, he presents data to suggest that such variables can contribute significantly to parole prediction. Examples of such variables include measures of "identification with criminal others" and "orientation to criminal means." Dean found that the part of reality which was represented by such theoretically-derived measures was independent of, and unaccounted for by, the usual actuarial predictors of recidivism on parole. While none of these purely "theoretically-derived" variables is included in the present study, it would seem that the predictor variables of criminal history, age, current offense, and substance abuse history which _are_ included have considerable _logical_ (or "content") validity in addition to their established empirical (or "predictive") validity.

Base rates. For the past 30 years, the difficulty of predicting statistically rare events has been documented in the literature (Gottfredson, 1967; Loeber & Dishion, 1983;

Meehl & Rosen, 1955; Sanchez, 1984; von Hirsch & Gottfredson, 1983/1984; Wilkins, 1980; Zwanenburg, 1977). Not only is a larger target (i.e., more frequent event) easier to hit (predict), but as base rates approach 50 percent it becomes easier to improve upon estimates based on no predictive information. If the base rate of a given event is, say, 2 percent one could safely predict that such an event will _not_ occur and be correct 98 percent of the time. Monahan (1981) has stated, "It is clear that knowledge of the appropriate base rate is the most important single piece of information necessary to make an accurate prediction" (p. 60). He attributed the superiority of results in several Michigan studies (over a group of California studies) to a base rate of violent criminal behavior in Michigan which was 2 to 35 times higher than base rates reported in the California studies he reviewed.

Selection ratio. In any selection problem some individuals are chosen and others are rejected. The selection ratio is the number who are chosen relative to the total number available. Gottfredson (1967) has noted that if the selection ratio is low, relatively low validity coefficients for a predictive device will suffice, whereas if a large proportion of offenders are to be accepted for parole, higher predictive validity would be required in order to be useful. This problem is somewhat related to the "false positive" problem discussed earlier. Most selection devices are more capable of predicting the behavior of individuals at the extremes than of those in the middle of a distribution (Gendreau, et al., 1980). When one is required to select only those individuals at the extremes, one is less likely to make false positive predictions than if one is required to predict the behavior of offenders in the middle of a distribution.

The Accuracy of Prediction

A number of methods and statistics for assessing the accuracy of predictions have been reported in the literature, including (a) Mean Cost Rating (MCR), (b) Improvement Over Chance (IOC), and (c) explained variance (R^2). Each of these measures is discussed briefly in this section.

MCR. One cannot read through a dozen good studies on the prediction of recidivism without encountering references to Mean Cost Rating (MCR). Consistent use of this measure has facilitated the comparison of predictive models and instruments (Simon, 1971; State of Iowa, 1984a; Wentz & Oldroyd, 1979; Zwanenburg, 1977). Fischer (1985) noted that MCR was a particularly good measure of predictive accuracy when a dichotomous criterion variable was involved. The essence of the measure was developed by Duncan, Ohlin and Reiss (1953) and Glaser (1954), and further refined by Inciardi, Babst and Koval (1973).

In order to simplify the calculation of MCR, Inciardi, et al. (1973) derived formula 1, below:

$$MCR = \sum_{i=1}^{k} C_i U_{i-1} - \sum_{i=1}^{k} C_{i-1} U_i \tag{3.1}$$

where K = Total number of categories [of predictor variable(s)],
i = Each specific category [of predictor variable(s)],
C = Cost,
U = Utility.

Details of computations and an example are provided in the next chapter. Inciardi, et al. (1973) note a number of reasons why this measure has been used so consistently in prediction research: First, unlike chi-square which requires identical degrees of freedom for comparisons across variables or between instruments, MCR can be used to compare items with alternative numbers of categories. Another reason is that, unlike the J value (ranking cases by their increasing probability of success), MCR can be used in configural analysis. Finally, unlike The Index of Predictive Efficiency which tends to fluctuate depending on the value of total group outcome rates, MCR can be calculated and retain selectivity regardless of the outcome rates in the subcategories.

Improvement Over Chance (IOC). In any predictive study a certain percentage of correct predictions can be made by chance alone. One measure which has been used to correct for chance accuracy in predictions of recidivism is Improvement Over Chance (IOC) (Sanchez, 1984). The equation for this measure is given below (3.2) as provided by Sanchez (1984):

$$IOC = OCV - RCV \qquad (3.2)$$

$$OCV = VP + VN$$

RCV = predicted by a random selection of subjects on the basis of the marginal values in a prediction table,

where,
IOC = Improvement Over Chance,
OCV = Observed Correct Values,
RCV = Random Correct Values (Sum of correct predictions expected by chance alone).
VP = Valid (True) Positives,
VN = Valid (True) Negatives.

Explained variance (R^2). The most common measure of predictive accuracy used when powerful linear, additive, multivariate techniques are used is R^2 (the square of the multiple correlation coefficient) which is often referred to as the "proportion of explained variance" (Gottfredson, 1967). This value is also referred to as the "coefficient of determination" and its complement ($1-R^2$) as the "coefficient of alienation" (proportion of unexplained variance in the criterion variable). This measure of predictive efficiency will be considered further in the next section.

Cross-validation. Predictive models or instruments are developed on one population or sample and need to be cross-validated on a new or different sample. Cureton (1950) provided one of the most incisive criticisms of predictive instruments or models which are not cross-validated. He exposed a sample case as nothing more than a random collection of nonsense by subjecting it to cross-validation. Gottfredson (1967) outlined a series of five steps to be followed in the completion of any prediction study: (a) establish criterion categories for "favorable" and "unfavorable" parole performance, (b) define and select attributes or characteristics upon which predictions are to be based, (c) determine relationships between criterion categories and predictor candidates in a sample representative of the population for which inferences are drawn, (d) verify the relationship determined on the basis of the original sample by application of the prediction procedures to a new sample from the population, and (e) apply the prediction methods in situations for which they were developed. Mosier (1951) considered the procedures in steps (c) and (d) in greater detail.

Jackson (1971) and Anastasi (1976) have both noted that rationally (logically, theoretically) constructed prediction models or instruments are less likely to exhibit extensive "shrinkage" in predictive accuracy when cross-validated than those which are purely empirically developed. As mentioned, the predictors selected for inclusion in this study have considerable rational (theoretical) justification in addition to being empirically well established as predictors. In light of this, little shrinkage is expected upon cross-validation.

The Combination of Predictors

Unit weighting. The earliest method of combining predictor variables, which has come to be known as "the Burgess technique," involved unit weighting of factors found to be associated with "favorable" parole outcomes in subpopulations of offenders (Bruce, Harno, Landesco & Burgess, 1928; Warner, 1923). This technique required tabular data, many predictors and no differential weights for predictors.

It was modified and streamlined by later researchers but the unit weighting scheme, if used with few predictors was criticized by Gottfredson (1967).

Bivariate correlation. Sheldon and Eleanor Glueck (1950) are credited with the next major breakthrough in methodological and statistical developments concerning prediction of recidivism. They weighted each item (predictor) according to the bivariate correlation coefficients between each predictor and the criterion. The problem with this, as Gottfredson (1967) has noted, is that they did not account for intercorrelations between predictors. The method was not found to be superior to assignment of unit weights.

Multiple linear regression and linear discriminant function. The development of multiple linear regression and linear discriminant function analyses constituted the next major breakthrough. These methods take into account both intercorrelations of predictor variables and correlations of predictors with criterion variables. Gottfredson (1967) cites a number of studies in which these techniques were found to be more effective than unit weighting techniques. Major advantages of regression analyses include: (a) the capability (theoretically) to optimally weight predictors to maximize the accuracy of predictions, (b) the ability to determine proportionate reduction in unexplained variance of each variable entered into regression or discriminant equations, and (c) the ability to reduce the number of predictors with only a slight loss in predictive accuracy (Dean, 1968). Limitations include assumptions of linearity, homoscedasticity additivity and normality and the marked tendency of these techniques to "over-fit" to samples. Considerable shrinkage in predictive accuracy is often evident with cross-validation.

There have been a good number of recent successful recidivism prediction applications of multiple linear regression analysis (Gendreau, et al., 1980; Petersilia & Honig, 1980; Sanchez, 1984; Wentz & Oldroyd, 1979) and linear discriminant analysis (Bonham, et al., 1984; Godfrey & Schulman, 1972). Zwanenburg (1977) and Gottfredson and Gottfredson (1980) have all noted a number of cases, however, in which equally or unweighted combinations of predictors are as good, or better than weighted predictors in terms of the amount of "shrinkage" observed on cross-validation.

In many recidivism prediction studies the dependant variable is binary (dichotomous). Examples include successful versus unsuccessful parole outcome, arrest versus no arrest for violent felony while on parole, etcetera. Dobson (1983), Engelman (1983) and Lee (1980) have noted that the most appropriate statistical analyses when a dichotomous criterion variable is being predicted include multiple linear discriminant analysis and logistic regression. Press and Wilson (1978) report that stepwise logistic regression provides a higher correct classification rate, upon cross-validation than discriminant analysis when independent variables are not normally distributed, covariance matrices are not identical and independent variables are dichotomous. Since many of the independent (predictor) variables in this study are dichotomous, and the two key dependent (criterion) variables are dichotomous, stepwise logistic regression was selected for most of the analyses.

The only recidivism prediction study which reported the use of latent trait methodologies was Wainer and Morgan (1982). The dichotomous criterion was 'successful' versus 'unsuccessful' parole outcome and the predictors were nine dichotomous items from the original Salient Factor Score (SFS). When results using this model were compared with results using a standard linear model after cross-validation they found the latent trait model to be considerably superior (38 compared to 44 out of 100 total errors). It seems particularly odd that so few studies report the use of a logistic model rather than a multiple linear regression or discriminant model when so many variables in criminological research are dichotomous.

Whenever results of multiple regression analyses were reported in detail most of the well-known "stable" predictors of recidivism were found to be those which explained the greatest proportions of variance in criterion variables. Gendreau, et al. (1980) reported that the dichotomous items "to court before age 16," "born outside Canada" and "any current drug offenses" were all related to the criterion of reconviction within two years of parole the criterion of reconviction within two years of parole release, with observed p-values less than .01. The combination of these variables yielded a multiple R of .45 and an R^2 of .20 on the cross-validation sample of 400 cases. Monahan (1978) reports a series of studies involving up to 7,000 parolees, in which several multivariate regression equations were calculated, but, as he reports, "none was even hypothetically capable of doing better than an 8-to-1 false-to-true positive ratio" (p. 247).

Results of studies in which discriminant analysis has been applied are slightly more encouraging than those in which multiple linear regression has been used. Bonham, et al. (1984) tested the ability of 20 variables to predict the dichotomous criterion of parole success (discharge during two-year follow-up period) versus parole failure (warrants issued for technical violations or new charges or extension of parole past the two-year follow-up period). Using a sample of 350 Kansas inmates released on parole between March and September 1979, nine of the first 13 variables met the criteria for inclusion in the discriminant function equation, with a final Wilks' Lambda of .87 ($P < .001$). These variables were: recidivism risk, program utilization, institution behavior, inmate attitude, time served, community attitude, substance abuse, prior criminal record and seriousness of crime. These items were rated on a one to four scale by members of the Adult Authority at Kansas state parole hearings (reliability estimates or further details of these items are not provided). The four highest canonical discriminant function coefficients corresponded to recidivism risk (.590), program utilization (.344), inmate attitude (-.347), and institution behavior (.316). The four variables which failed to enter the equation included: mental/physical health, parole plan, total risk score and history of violence. The authors state that 68.3 percent of the cases were correctly classified using the final equation (parole recidivism base rate of 37.1 percent), but since there is no mention of cross-validation this is likely an inflated value. Further, Box's M (99.44, p<.001) indicated unequal covariance matrices, thereby potentially declaring discriminant analysis an inappropriate procedure for these data.

Six of the eight secondary variables in the same study qualified for inclusion in a different discriminant equation (final Wilks' Lamda of .86, p<.001). These variables included the following (standardized canonical discriminant function coefficients in parantheses): prior incarcerations in Kansas (.767), drug usage (-.451), age of inmate at hearing (-.642), months served on sentence (.597), class of felony (.316), and alcohol usage (-2.11). Type of offense and last grade completed failed to enter the equation.

Configural analyses. The next group of statistical and methodological developments involved a series of configural techniques, beginning with Glaser (1964). This method involves the successive partitioning of a sample into subgroups on the basis of a single item found in each subgroup to have the closest association with the criterion; that is, the single most predictive item is found and the total sample is divided on this attribute. This process is repeated until no further items significantly distinguish subgroups. An example is provided in Figure 3.2. Gottfredson (1967) and Gottfredson and Gottfredson (1980) report that generally these methods have been found to be equivalent, but not superior in predictive efficiency to linear models. Other configural techniques include "predictive attribute analysis" and "association analysis".

When various unit weighting, linear and configural analyses are compared for predictive efficiency, they consistently seem to perform (approximately) equally well (Gottfredson & Gottfredson, 1980; Simon, 1971; Wormith & Goldstone, 1984). Suggested reasons for this apparent equality have revolved around the low level of measurement (ordinal or categorical) of data available for large-scale criminological research. When such data are <u>also</u> severely restricted in range (as is often the case for both predictor and criterion variables), the more statistically powerful linear techniques are limited in their efficiency. Von Hirsch and Gottfredson (1983/1984) bemoan the repeated finding that even with powerful multivariate analyses for combining predictors, the proportion of explained variance in recidivism has consistently remained between 15 percent and 30 percent. Sanchez (1984) writes, "I am not impressed

<table>
<tr><td colspan="4">A. No prior commitments
77% Success</td><td colspan="8">B. One or more prior commitments
59% Success</td></tr>
<tr><td rowspan="5">AA. Over 35 at release</td><td colspan="2">AB. 24-35
78% Success</td><td rowspan="5">AC. 23 or younger</td><td colspan="6">BA. Satisfactory prison adjustment
64% Success</td><td colspan="2">BB. Unsatisfactory prison adjustment
42% Success</td></tr>
<tr><td rowspan="4">ABA. 3 + years on longest job</td><td rowspan="4">ABB. Less than 3 years</td><td rowspan="4">BAA. Longest job 4 + years</td><td colspan="5">BAB. Longest job under 4 years
62% Success</td><td rowspan="4">BBA. Employed more than 25%</td><td rowspan="4">BBB. Employed less than 25%</td></tr>
<tr><td colspan="3">BABA. Never violated parole
66% Success</td><td colspan="2">BABB. Violated parole
51% Success</td></tr>
<tr><td colspan="2">BABAA. 31 + years at release
72% Success</td><td rowspan="2">BABAB. Under 30</td><td rowspan="2">BABBA. 19 + at first arrest</td><td rowspan="2">BABBB. Less than 19</td></tr>
<tr><td>BABAAA Less than 2 crimes</td><td>BABAAB More than 2 crimes</td></tr>
<tr><td>93% Success</td><td>85% Success</td><td>76% Success</td><td>64% Success</td><td>79% Success</td><td>78% Success</td><td>67% Success</td><td>60% Success</td><td>58% Success</td><td>47% Success</td><td>50% Success</td><td>34% Success</td></tr>
</table>

Figure 3.2. Glaser's Initial Configural Table.

Note: From The Effectiveness of a Prison and Parole System by D. Glaser, 1964, Indianapolis, IN: Bobbs-Merrill, (p. 253).

by a set of variables that, at best, account for one-fourth of the variance in the dependent variable" (p. 191).

A number of very promising new methods and statistics for criminological research have received little, if any, attention. These include: (a) manual analysis of cases (Fischer, 1985), (b) prediction analysis developed specifically for ordinal data (Hildebrand, Laing & Rosenthal, 1977), and (c) use of latent trait estimators (Wainer & Morgan, 1982).

Manual analysis. In addition to computer analyses, Fischer (1985) and his associates examined 400 criminal files manually. Two stacks of cases were analyzed, one constituting those with either a new violent felony charge or a new prison sentence for a "safety" crime (violent, property, weapons and drug felonies), and the other including those not satisfying this criterion. Fischer (1985) reports that from a manual analysis of risk factors and from a subsequent check with computerized data, he determined that a number of items constituted highly efficient predictors of serious recidivism and violence in the study sample. It is somewhat ironic that research methods have, in this case, come "full circle" from the original research by Burgess and his colleagues. From results of an earlier cross-validation of some of these specific risk factors on a Michigan sample (Murphy, 1985), it seems apparent that Fischer overlooked the extremely low base rate of some of his "special risk" factors. This oversight should not discourage future researchers from embarking on large-scale manual analyses of cases. More stable and robust "special risk" factors may yet be identified by this means.

Prediction analysis for ordinal data. As mentioned at several points in this literature review, most actuarial data in criminology is ordinal in nature. In response to the need for more precise techniques for analyzing such data, Hildebrand and his colleagues (1977) developed a technique which they have termed "prediction analysis." This method uses crosstabulations in a manner similar to chi-square analysis: observed cell frequencies are compared with expected (by chance) cell frequencies. Very precise predictions can be made and statistically tested using this approach. To date, no applications of this promising technique to criminological data have been made.

Latent trait estimation. Wainer and Morgan (1982) have attempted to apply latent trait theory to criminological data. They compare latent trait with standard linear response functions for a 9-item prediction scale (the federal Salient Factor Score) and compare the cross-validated accuracy of a standard Rasch estimator with a much more robust estimator, referred to as "AMJACK." One of the major advantages of using a latent trait model is that numerical predictions of recidivism (for example, 25 or 85 percent probabilities) can be given for each parolee, rather than merely rankings of groups of offenders according to their <u>relative</u> likelihood of committing future crimes (for example, "excellent" or "very poor" risk categories). With only nine items (predictors) the latent trait model was found to be superior in predictive accuracy to a standard linear model and the "AMJACK" estimator was found to be considerably superior to a standard Rasch estimator. Promising possibilities for future research using this approach include the application of the latent trait model and robust estimator to criminal history, whereby total past arrests (up to the maximum number for offenders in the population sampled) could be scored dichotomously as "items" measuring a single latent trait. These recent advances seem worthy of further investigation.

<u>Recidivism Prediction Models and Instruments</u>

Prediction tools or instruments for parole risk assessment are based on models, which are classification systems. Regarding the importance of classification in criminal justice, Solomon and Baird (1981) stated the following:

> Corrections must recognize that classification is first and foremost a management tool. It should, in fact, be perceived as the veritable cornerstone of correctional administration. As a means of setting priorities, its purposes are to promote rational, consistent, and equitable methods of assessing the relative needs and risk of each individual and then to assign agency resources accordingly. (p. 4)
>
> ...Everyday, [sic] decisions are made regarding the potential for violence, protective custody requirements, program needs, and, in probation, parole, and community programs, the relative risk of recidivism posed by each client. The criteria on which these decisions are based must be explicitly delineated

> and defined and readily defensible. Unstructured and ill-defined classification procedures can no longer be tolerated in corrections. (p. 6)

According to Rans (1984), a "model" is:

- A (logical and/or mathematical) representation of a relationship that predicts future behavior in a "system," and
- A statement of assumptions about the "system" and its environment, and about the values, constraints and relationships which shaped the model's development. (p.1)

In this section of the literature review the reader is provided with information regarding current reidivism risk assessment models.

Recidivism Risk Assessment: Current Models and Instruments

Detailed information regarding predictor and criterion variables within many of the recent parole risk assessment models was provided in Chapter II. This brief section is intended as a supplementary framework in which earlier material can be integrated.

Federal Salient Factor Score (SFS). One of the major existing risk assessment models was developed over 12 years ago and was originally referred to as the "Salient Factor Score" (Hoffman & Beck, 1974). The U.S. Parole Commission revalidated the model on a sample on 1,260 federal prisoners released in 1976, six years after the sample for the original instrument. Results have indicated that the SFS retained its predictive power (Hoffman & Beck, 1980). The SFS has showed MCR values in the .35 range on federal data (Hoffman & Adelberg, 1980; Hoffman & Beck, 1974). Once revalidated, the instrument was further promoted by Hoffman and his colleagues (Hoffman & Adelberg, 1980; Stone-Meierhoefer & Hoffman, 1982). In 1981 employment stability was dropped as a predictor from the SFS, new weights were assigned to predictors and the instrument was subsequently cross-validated on a sample of 2,289 released federal prisoners. It has since been referred to as "SFS 81" (Hoffman, 1983). Both the Salient Factor Score (SFS) and SFS 81 have been used in several major research projects, including applications of latent trait theory (Wainer & Morgan, 1982) and investigations of the relationship between offender age and prior criminal record (Hoffman & Beck, 1984).

Appendix A provides the reader with copies of these and other instuments currently used to predict recidivism risk for parolees. Figures A-1 and A-2 are the original (SFS) and revised (SFS 81) versions of the Salient Factor Score, respectively. Very few comparative evaluations of the predictive efficiency (as measured by MCR) of these risk assessment devices have been made. In Iowa, the Statistical Analysis Center in the Office for Programming and Planning has conducted a series of evaluations, based on an Iowa sample of 814 parolees (Fischer, 1985; State of Iowa, 1984a; 1985a). Base rates for the sample are as follows: (a) arrests for post-release violence--20 percent of offenders in the sample are arrested on parole, (b) most recent (current offence) sentence for violent felony--32 percent, (c) composite recidivism (a <u>or</u> b)--37 percent (these measures overlap), and (d) arrests for any felony offense--49 percent. Criterion (d) was included because, as Fischer (1985) has stated, "most of the models developed outside Iowa are inherently disadvantaged since they were not constructed to predict violence" (p. 75). Gottfredson and Gottfredson (in press) criticize the comparisons made by the Iowa Statistical Analysis Center, noting that comparisons of all models are made using the Iowa data, providing an advantage to the model developed on those data. In spite of these apparent weaknesses, estimates of MCR from this series of evaluations will be reported in this review, primarily because in most cases no other comparative data are available.

The 1984 evaluation of SFS 81 (State of Iowa, 1984a) reports values of MCR of .40, .40 and.44 for criteria (a), (b) and (c), respectively (criterion d was not included in 1984). For some unexplained reason, reports of 1985 evaluations (Fischer, 1985; State of Iowa, 1985a) list MCR values of .46, .45, and .45 on the <u>same sample</u> of 814 parolees using the same criteria! MCR for criterion (d) is listed as .41 (State of Iowa, 1985a).

<u>Illinois Dangerousness and Adjustment Scales</u>. Since 1979 the Illinois Department of Corrections and its researchers collaborated with consultants from the National Institute of Corrections to produce, among other instruments, their Dangerousness Scale and Adjustment Scale. Results from these scales are combined to produce a security designation with a violence risk assessment for institutional

with a violence risk assessment for institutional classification (Rans, 1984). Although these scales technically constitute a prison classification rather than a community release classification, they are included in this review because they provide a violence risk assessment. Other research relative to these scales is discussed in Rans (1982) and Fowler (1983). The reader is referred to Appendix Figure A-3 for copies of the Illinois Dangerousness and Adjustment Scales.

Ratings of predictive accuracy by the Iowa Statistical Analysis Center on their sample of 814 parolees were reported as MCR's of .36, .37 and .38 for criteria (a) post-release arrest for violent offense, (b) current offense prison sentence for violent felony, and (c) a <u>or</u> b, respectively (State of Iowa, 1984a).

<u>INSLAW Scale</u>. The Institute for Law and Social Research in Washington, D.C. (INSLAW) has pursued an extensive and rigorous research program resulting in the INSLAW Scale for selecting "career criminals" (Forst, et al., 1983; Williams, 1979). Appendix Figure A-4 is a copy of the scale. MCR evaluations by the Iowa Statistical Analysis Center are listed as .53, .53 and .54 for criteria (a), (b) and (c), respectively (State of Iowa, 1984a). MCR's for the same sample of 814 parolees, using the same criteria are listed in 1985 publications as .55, .53 and .54 for criteria (a), (b) and (c), respectively (Fischer, 1985). The value of MCR for criterion (d) is .43. It is difficult,

if not impossible, to determine which of the following reasons, if any, is responsible for the relatively high values of MCR reported in the Iowa comparison for this scale: (a) similarity of INSLAW and Iowa construction samples; (b) similarity of criterion measures used in the development of INSLAW and Iowa Scales; or (c) actual superiority in predictive efficiency of the INSLAW Scale over other current competitors of the Iowa Model.

Michigan Risk Screening. A random sample of 1472 parolees (37 percent of the population) released by the Michigan Parole Board in 1971 was studied extensively (350 variables analyzed), resulting in the development of the Michigan Assaultive and Property Risk Screening checklists (see Appendix Figures A-5 and A-6). Details of this research are presented in a comprehensive report by the Program Bureau of the Michigan Corrections Department (State of Michigan, 1978) and practical benefits of the screening instruments are reported by Fowler (1983). These instruments were revalidated by Murphy (1980) and, as noted by Monahan (1981), recidivism prediction accuracy was only slightly less dramatic than the original study. Actual recidivism rates (violent crime) for each prediction category are given as follows: (a) very low risk--8.9 percent, (b) low risk--11.1 percent, (c) middle risk--17.4 percent, (d) high risk--27.9 percent and (e) very high risk--32.0%. (The overall base rate for violent criminal recidivism in the sample was 16 percent).

Evaluations of predictive efficiency by the Iowa Statistical Analysis Center, combining the Michigan Assaultive and Property Risk Screening instruments, are not particularly high compared to other models assessed. MCR's of .40, .36 and .38 are reported for criteria (a), (b) and (c), respectively (State of Iowa, 1984a). In State of Iowa (1985a) comparison tables, values of MCR of .40, .37, .37 and .32 are listed for criteria (a), (b), (c) and (d) respectively. Again, however, one must consider that these evaluations are based on Iowa, and not Michigan, data. On Michigan data, these instruments exhibit MCR's in the .40 range (Murphy, 1980; State of Michigan , 1978).

Oregon Criminal History/Risk Assessment. Appendix Figure A-7 is a copy of the 1980 version of this instrument for review. Values of MCR of .32, .42, and .40 are reported for criteria (a), (b) and (c), respectively, by the Iowa Statistical Center (State of Iowa, 1984a). In the 1985 comparison tables, values of MCR of .42, .42, .40 and .40 are given for criteria (a), (b), (c), and (d), respectively (State of Iowa, 1985a).

RAND 7-Factor Score. The RAND Corporation sponsored a major research project involving an approximation of a nationally representative random sample, which included studies of inmates in correctional institutions from California, Texas and Michigan. Summaries of results from this research are provided by various members of the RAND Corporation research staff (Chaiken & Chaiken, 1982a; 1982b;

Greenwood, 1982; Petersilia, Greenwood & Lavin, 1977; Petersilia & Honig, 1980). The RAND 7-Factor Scale was developed using a sample of 781 inmates whose current offense of conviction was either robbery or burglary (Greenwood, 1982). The reader is referred to Appendix Figure A-8 for review of the seven predictive "factors" included in this instrument. Fowler (1983) provides a brief neutral commentary on the scale but von Hirsch and Gottfredson (1983-84) severely criticize it primarily for the following reasons: (a) cross-tabulations within the same sample rather than samples collected at different times were used to "predictively" validate the instrument and (b) the "false positive" and "false negative" prediction rates were 56 percent and 16 percent, respectively, on the original sample.

Evaluations by the Iowa Statistical Analysis Center include MCR's of .40, .43 and .43 for criteria (a), (b) and (c), respectively. Results reported in the State of Iowa (1985a) comparison tables include MCR values of .44, .43, .43 and .38 for criteria (a), (b), (c) and (d), respectively. Fischer (1985) computed MCR's of .40 and .41 on the 7-Factor Scale, using <u>RAND</u> data.

<u>Utah History/Risk Assessment</u>. Contrary to most of the other recidivism prediction devices, this instrument was primarily rationally rather than empirically developed. Anthony and Oldroyd (1979) and Wentz and Oldroyd (1979) completed cross-validations of the instrument with 70 and

100 cases respectively. In the latter study it was found that only 5 of the 11 variables in the scale were (statistically) significantly related to successful completion of parole. The reader is referred to Appendix Figure A-9 to review the 11 variables included in the instrument. Anthony and Oldroyd (1979) report that although the scale correlated with successful completion of parole only .42 (18 percent of variance explained) predictive accuracy of the instrument was still higher than that of the Federal Salient Factor Score. Since the study did not use any standard measure of predictive efficiency, such as MCR, however, the basis for their comparison is unclear.

Wisconsin Risk Assessment. The Wisconsin Model is the result of four years of research which began in 1975, with substantial funding and provision of resources from the Law Enforcement Assistance Administration (LEAA) and the Bureau of Community Corrections. The reader is referred to Appendix Figure A-10 to review the Wisconsin Risk Assessment. Baird (1981) provides an overview of the entire Wisconsin Model including its application within the criminal justice system in the state, and results of a validation study in which considerable accuracy is demonstrated predicting parole failures. On a sample of 8,251 parolees, percentages of parole revocations are given for each Risk Assessment level: (a) low risk--3.0 percent, (b) moderate risk--10.0 percent, (c) moderately high risk--22.2 percent, and (d) high risk--37.1 percent.

Evaluations by the Iowa Statistical Analysis Center include MCR's of .43, .35 and .35 for criteria (a) arrest for violent criminal recidivism, (b) currennt offense prison sentence for violent felony, and (c) criteria a <u>or</u> b, respectively (State of Iowa, 1984a). State of Iowa (1985a) comparison tables report MCR's of .44, .35, .36 and .31 for criteria (a), (b), (c) and (d), respectively.

<u>Iowa Offender Risk Assessment</u>. Under the direction of Daryl Fischer, a Ph.D. mathematician, the Iowa Statistical Analysis Center in 1975 embarked on a long-term research project using data on released probationers and parolees in Iowa. According to Fischer (1985), "using a data base of over 6400 cases, a variety of alternative measures of probation/parole outcome, and a variety of offender characteristics to serve as potential predictors, [He] and [his] colleagues devoted over 3000 hours of staff time and over $300,000 in federal funding to recidivism research and to the development of risk assessment instruments between 1975 and 1980" (p. 11).

The end product was a device termed the "Iowa Offender Risk Assessment Scoring System" (Fischer, 1980; State of Iowa, 1983b). which incorporated both violence and general recidivism prediction instruments. This system was cross-validated against a sample of 9,378 probationers and parolees released in the late seventies, resulting in values of MCR between .55 and .65 (Fischer, 1985; State of Iowa, 1984b).

The impact of the objective risk prediction system upon the rate of violence among parolees after 21 months of experience with the parole guidelines was very encouraging (State of Iowa, 1983a; Fischer, 1983a). While they were able to increase paroles per month by 52 percent during the study period (over the preceeding 27 months), they were simultaneously able to reduce the rate of violence among parolees by 35 percent.

In early 1983, the Iowa Statistical Analysis Center (SAS) streamlined the original version of the Model. The Iowa SAS selected a sample of 1000 offenders released from Iowa prisons by parole or expiration of sentence during the years 1976-1980. A four-year follow-up was undertaken. Of the 1000 cases in the sample, 814 constituted the construction sample and 186 served as the cross-validation sample for the 1983 version of the Iowa Model. In addition to computer analysis, 365 cases were manually examined resulting in the identification of 24 "Special Risk Factors" (State of Iowa, 1983b).

The 1983 version of the risk assessment model provided a much better split between good and bad risk categories (reducing "medium" or "fair" risks). The 1983 version also substantially reduced Type II error (over prediction, or "false positives"). The 1983 version has been cross-validated in seven States and Canada. To date, results of cross-validation studies are available only for the District of Columbia and Michigan. Murphy (1985) quotes the unpublished report of the replication study (1983 version of the Iowa Model) by the Department of Corrections in Washington, D.C., as follows:

> ...There was no association between what the tool predicted and arrests for violent offenses...We conclude, therefore, that the tool is of limited value in the District of Columbia...and...should not be used as a means of identifying individuals for early parole release. (p. 6)

Murphy (1985) summarizes results of the Michigan replication study of the 1983 version as follows:

> When the Iowa Risk Assessment Model was applied to the sample of Michigan parolees, the results indicated that the Iowa Model: (a) did not replicate the violent risk groups in the predicted order; (b) did not significantly differentiate between failure rates; and (c) had relatively low discriminatory power.
>
> Although the property prediction table produced significantly different failure rates, only the Very Good and Poor risk groups had failure rates in the predicted direction. The Good and Fair risk groups had similar failure rates.
>
> These results indicate that the Iowa Risk Assessment Model did not validate adequately on the sample of Michigan parolees and, therefore, cannot be generalized to the Michigan prison population. (pp. 1-2)

Due to a consensus of observers that the 1983 version was still too complicated to be used reliably, the SAS instituted further efforts to streamline the model.

The 1984 version was developed on the same 814-case sample used to construct the 1983 version, and cross-validated using the same 186 remaining cases from the 1000-case sample described earlier. Values of MCR of .70, .62, .66 and .51 are reported (on the <u>construction</u> sample of 814 cases) for criteria (a) arrest for violent criminal recidivism, (b) current offense sentence for violent felony,

(c) a <u>or</u> b, and (d) arrest for felony on parole, respectively (State of Iowa, 1985a). MCR's for the <u>cross-validation</u> sample of 186 cases are .69, .67 and .66 for criteria (a), (b) and (c), respectively (Fischer, 1985).

The reader is referred to Appendix Figures A-11 and A-12 for copies of the coding forms for the 1984 and 1985 versions of the Iowa Model, respectively. In comparing the coding forms and procedures for the 1984 and 1985 versions, the reader will note that, apart from modification of the scores assigned to the composite variables X and Y, these models are identical. Results for the 1985 version in terms of predictive efficiency are only provided for the construction sample of 814 offenders (State of Iowa, 1985a). Values of MCR of .71, .61, .65 and .50, for criteria (a), (b), (c) and (d), respectively.

Chapter Summary

Prediction of recidivism and violent criminal behavior seems fraught with methodological problems, but still holds considerable promise for future research. Although a "hard core" group of recidivistic criminals has been consistently identified, "false positive" predictions still outnumber "true positive" predictions approximately three-to-one. Differential weighting of prediction outcomes according to social consequences seems appropriate. The accuracy of actuarial predictions consistently exceeds that of clinical techniques. The present study is actuarial in nature.

Most criminal justice data extracted from administrative files has been criticized for being "static," empirically rather than rationally (theoretically) selected, and confounded with legal categories. Methods for overcoming most of these limitations have been suggested and, to the greatest extent possible, incorporated into this study. The importance of identifying base rates and the difficulty in predicting low-base rate events has been stressed. Base rates for general recidivism in the sample selected for this study come close to meeting "ideal" standards for criterion base rates; however, the base rate for violent criminal recidivism will likely make accurate prediction of criminal violence of parolees difficult.

A number of methods of assesssing predictive accuracy and efficiency were discussed, including computations of mean cost rating (MCR), Improvement Over Chance (IOC) and explained variance. All of these techniques are incorporated into this study. Methods of combining predictors which were reviewed included unit weighting, bivariate correlation, multiple regression, discriminant function, stepwise logistic regression and configural analysis. Most studies comparing these techniques for predictive efficiency have concluded that they are approximately equal; however, multiple linear regression and linear discriminant function analyses have the advantage of allowing part correlation to assess the relative contributions of each predictor to explained variance in the criterion.

It was determined that the most powerful and appropriate techniques for analysis of relationships between a dichotomous criterion variable (such as the presence or absence of arrest for a violent felony on parole) and either continuous or dichotomous criterion variables are discriminant analysis and stepwise logistic regression. Of these two, logistic regression has been found to be more powerful when predictor variables are dichotomous. Since this is the case for many of the variables in this study, stepwise logistic regression was selected for use for the majority of analyses.

Promising techniques for <u>other</u> future research include large-scale manual analysis of cases, prediction analysis for ordinal data, and applications of latent trait theory.

Current recidivism risk assessment models and instruments are the Federal Salient Factor Score (SFS 81), the Illinois Dangerousness and Adjustment Scales, the INSLAW Scale, the Michigan Assaultive and Property Risk Screening Checklists, the Oregon Criminal History/Risk Assessment, the RAND 7-Factor Score, the Utah History/Risk Assessment, the Wisconsin Risk Assessment and the Iowa Offender Risk Assessment. Comparative evaluations of the predictive accuracy and efficiency of these recent parole risk assessment instruments are scant, at best. Fowler (1983), Rans (1984) and Stageberg (1983) present information on a number of these instruments, but rather than providing independent assessments of the reliability and validity of these devices, these authors merely cite the reports and tables presented by original developers of the models. The Iowa Statistical Analysis Center (Fischer, 1985; State of Iowa, 1984a; 1985a) provides detailed comparative analyses of these scales but they are biased in favor of the Iowa Model because Iowa data and outcome measures are used. More impartial and believable comparisons of these recent parole recidivism indices await future research.

CHAPTER IV

Methods

Chapters II and III were included to provide rationales for seclection of variables, methods and models for the study. In this chapter, descriptions of the sample, operational measures, design, testable hypotheses, and data analyses are provided.

Sample

Selection of Cases

The study sample consists of 640 males randomly selected from the total population of 4,084 offenders paroled from adult correctional institutions throughout the state of Michigan (see map of institutions in Appendix B) from January 1, 1980 through December 31, 1980. This 15.7 percent sample was drawn by the Michigan Department of Corrections Program Bureau, using a table of random numbers. The sample was randomly divided into two subgroups of approximately equal size (317 and 323 cases, respectively).

Compliance with Human Subjects Research Standards

Procedures for selection of subjects, handling of confidential data and recording of parolee information were submitted to, and approved by, the Michigan State University Committee for Research Involving Human Subjects (UCRIHS).

The study was approved under exempted research category "E", which includes research involving the study of existing data (all case information was originally collected by Michigan Department of Corrections research staff and recorded on offender file worksheets, copies of which are provided in Appendix C).

The major requirement for approval by the UCRIHS is that information be recorded in such a manner that subjects cannot be identified directly (by name) or by identifiers (such as prison number) linked to subjects. In meeting these conditions, the study also satisfies federal requirements for use of criminal justice data, and relevant criteria outlined in principle 9 of "Ethical principles of psychologists", published by the American Psychological Association (APA, 1981).

Demographic Characteristics

Demographic characteristics are presented for the two subsamples in Table 4.1. Comparisons of characteristics between these samples indicates that random assignment of cases resulted in groups with approximately equal summary statistics for each variable. It should be noted, however, that the base rates for both violent and general (either violent or nonviolent) felony arrests on parole are slightly lower for subsample II than for subsample I.

Table 4.1. Demographic characteristics of subsamples.

Characteristic	Subsample I (N=317)					Subsample II (N=323)				
	Valid Cases	Value Frequencies (Percent)	Mean	Mode	Standard Deviation	Valid Cases	Value Frequencies (Percent)	Mean	Mode	Standard Deviation
Age at Time of Parole	316	-	28.8	26.0	7.8	321	-	28.7	27.0	8.1
Age at First Criminal Arrest	315	-	18.0	17.0	4.6	320	-	17.3	17.0	4.4
Race	316		-	-	-	321		-	-	-
- White		132(42)					137(43)			
- Non White		184(58)					184(57)			
Marital Status at Current Offense	316		-	-	-	321		-	-	-
- Single (Never Married)		203(64)					206(64)			
- Other than Single		113(36)					115(36)			
Felony History	316		-	-	-	321		-	-	-
- No Prior Arrest		46(15)					36(11)			
- Prior Adult or Juvenile Arrest		270(85)					285(88)			
Base Rates for Felonious Recidivism	316		-	-	-	321		-	-	-
- Violent Felony Arrest on Parole		42(13)					34(11)			
- General (Either Violent or Non-violent) Felony Arrest on Parole		139(44)					131(41)			

Age at the time of parole ranged from a minimum of 18 years to a maximum of 70 years, across the samples. Age at first criminal arrest ranged from 7 years to 39 years. Measures of central tendency consistently indicate reasonably uniform distribution of age, with averages of approximately 27 years for age at parole and 17 years for age at first criminal arrest.

There are approximately 40 percent more nonwhites than whites across the samples, and individuals who were single (never married) at the time of their current offense outnumber those of any other marital status almost two to one. Finally, across the samples approximately 12 percent of the parolees were first offenders.

Operational Measures

As presented in Chapter II, there are five core variables of interest in the study: a) criminal history, b) current offense, c) substance abuse history, d) age and e) recidivism on parole. Operational measures have been presented in this section according to the variables with which they are associated.

Criminal History

Operational measures of criminal history are those listed in Table 4.2. Although the table is self-explanatory for the most part, a number of points seem worthy of mention: First, the reader should be careful to note the distinction between prior arrests, prior charges, prior convictions and prior sentences. Measures 2, 17 and 20

Table 4.2. Operational measures of criminal history.

Measure Number	Name of Operational Measure	Level of Measurement/ Coding Format
1	Number of years of street time since 14 yrs. of age	Interval/Continuous
2	Number of prior arrests	
3	Number of prior probations	
4	Number of prior adult jail terms	
5	Number of prior juvenile commitments	
6	Number of prior adult commitments	
7	Number of violent felony charges:	
8	Total number in last 12 months of street time	
9	Total number in last 24 months of street time	
10	Total number in last 36 months of street time	
11	Total number in last 5 years of street time	
12	Number of nonviolent felony charges:	
13	Total number in last 12 months of street time	
14	Total number in last 24 months of street time	
15	Total number in last 36 months of street time	
16	Total number in last 5 years of street time	
17	Evidence of juvenile felony	Categorical/Dummy Interval (1,0)
18	Property (nonviolent) disposition greater than 1 year	
19	Person (violent) disposition greater than 1 year	
20	Felony History	
21	Multiple different charges with single arrest	
22	Number of major non-bondable misconducts	Ordinal/None, 1, 2
23	Proportion of years of street time to years of calendar time since 14 years of age	Interval/Continuous

pertain to prior arrests; measures 7 through 16, 21 and 22 pertain to charges; and measures 1, 3 through 6, 18 and 19 pertain to sentences. This inclusion of indicators at various levels of proximity to actual criminal behavior was recommended by Monahan (1978).

Current Offense

Operational measures of current offense are listed in Table 4.3. The coding scheme used by the Michigan Department of Corrections Program Bureau for current offense (measure 1) was adopted. The coding scheme is provided in Appendix Figure D-3.

Substance Abuse History

Operational measures of substance abuse history are listed in Table 4.4. The Substance Abuse Scale is provided in Figure D-4 of the detailed coding instructions in Apprendix D. A collapsed version of this scale was also included in the study to determine whether or not groupings of the values according to similarity of substance would influence results. Subgroups of this collapsed ordinal scale were then coded to form a series of dichotomous substance abuse variables.

Age

Operational measures of age are those listed in Table 4.5. In addition to the measures of age at parole and age at first criminal arrest, age is incorporated indirectly into street time indices in Table 4.2 (primarily measures 1 and 23) since the older an offender is the more street and

Table-4.3. Operational measures of current offense.

Measure Number	Name of Operational Measure	Level of Measurement/ Coding Format
1	Current offense (Michigan coding)	Ordinal/Categories 1-34
2	Current escape or jailbreak	Categorical/Dummy Interval (1, 0)

Table 4.4. Operational measures of substance abuse history.

Measure Number	Name of Operational Measure	Level of Measurement/ Coding Format
1	Substance Abuse Scale	Ordinal/Categories 1 through 8
2	Collapsed Substance Abuse Scale	Ordinal/Categories 0 through 4
3	PCP/Sniffing volatile substance	Categorical/Dummy Interval (1, 0)
4	Problem use of chemical substances	
5	Any prior use of some form of chemical substance	
6	Prior abuse of some substance (including alcohol)	

Table 4.5. Operational measures of age.

Measure Number	Name of Operational Measure	Level of Measurement/ Coding Format
1	Age at parole release	Interval/Continuous
2	Age at first criminal arrest	

Table 4.6. Operational measures of recidivism on parole.

Measure Number	Name of Operational Measures	Level of Measurement/ Coding Format
1	Arrest for violent felony on parole	Categorical/Dummy Coded (1, 0)
2	Arrest for general felony on parole	

calendar time he can potentially amass during his "criminal history".

Recidivism on Parole

Operational measures of recidivism are include those listed in Table 4.6. The Michigan Parole Recidivism Score was developed by the Michigan Department of Corrections Program Bureau. The two most serious forms of arrest on this ordinal scale (violent and general or combined felonies) were collapsed into dichotomous "dummy" variables, since felonious recidivism is the criterion of greatest interest in the study.

As mentioned in the limitations section of Chapter I, reliability estimates of the operational measures (beyond intercoder agreement) are not available for the study sample since data were previously collected from offender files prior to this study.

Design

This is a predictive study involving stepwise logistic regression. Analyses were used to assess relationships between all operational measures of predictor variables and the dichotomous criterion measures of 'arrest for violent felony on parole' and 'arrest for general (violent or nonviolent) felony on parole'. The multivariate predictive equations resulting from these analyses on one subsample were then subjected to cross-validation using the other subsample. Six logistic prediction equations resulted: details of analyses are provided following the testable hypotheses.

Testable Hypotheses

1(a) Measures of criminal history are related to the criterion measure 'arrest for violent felony while on parole.'

1(b) Measures of criminal history are related to the criterion measure 'arrest for general felony while on parole.'

2(a) Measures of current offense are not related to the criterion measure 'arrest for violent felony while on parole.'

2(b) Measures of current offense are not related to the criterion measure 'arrest for general felony while on parole.'

3(a) Measures of substance abuse history are related to the criterion measure 'arrest for violent felony while on parole.'

3(b) Measures of substance abuse history are related to the criterion measure 'arrest for general felony while on parole.'

4(a) Measures of age are negatively related to the criterion measure 'arrest for violent felony while on parole.'

4(b) Measures of age are negatively related to the criterion measure 'arrest for general felony while on parole.'

5 A logistic regression model developed in this study for prediction of general felony arrest will provide parole recidivism predictions which result in a Mean Cost Rating equal to, or greater than, .40.

6 A logistic regression model developed in this study for prediction of violent felony arrest will provide parole recidivism predictions resulting in a Mean Cost Rating less than .40.

Data Analyses

There were essentially three steps in the analysis of data for the study: (a) preliminary coding, (b) analyses of relationships between individual variables, and (c) construction and evaluation of the logistic models.

It should be noted that there was a "fourth" step in data analysis, which included tests for violation of assumptions underlying some of the more common statistical analyses, including multiple linear regression, discriminant function and Pearson correlation. A series of statistical reference and software programming texts were consulted during this process, including Andrews, et al. (1981) Berry and Feldman (1985), Hayes (1981) and Norusis (1983). Although visual tests (including bivariate scattergrams and scatterplots of regression residuals against either predicted values or operational measures of predictor variables) did not indicate any gross violations of the assumptions of homoscedasticity or linearity, results of statistical tests (including (a) Cochrans C and Bartlett-Box F, for homoscedasticity; (b) skew and kurtosis statistics, for normality; and (c) ANOVA F-ratios for 'linear' and 'deviation from linear' components, for linearity) were more discouraging. When it was found that most of the operational measures of predictor variables failed to meet the assumptions of linearity, homoscedasticity and normality, alternative forms of analysis were sought. Rationales for selection of stepwise logistic regression are provided in this section of the chapter.

<u>Preliminary Coding</u>

Two sets of coding procedures were completed for the study: (a) those involving the development of machine-readable data for the earlier cross-validation of the 1983 version of the Iowa model by the Michigan Department of Corrections (Program Bureau), and (b) those involving recoding of the pre-existing data set from the Michigan Department of Corrections or creation of new variables from offender file worksheets.

Details regarding both sets of coding procedures are given in Appendix D. In an effort to reduce loss of data during coding, data entry, recoding and transformation, a number of procedures and safeguards were included. First the coding format for criminal history was specified in such a way that if entered data in any case was one column off, error messages would be activated later in data definition phases. Slashes were embedded in the data (American date format) fields. By this means a number of cases with data entered in inappropriate columns were located and the errors were corrected. In addition, the hand-coded criminal history data entry was verified by data entry technicians. At quite a number of points data files were written to disk and then read in as another file for further analysis. SPSS:X (SPSS Inc., 1986) provides a safeguard to alert the user to incorrect write-format specifications by printing asterisks in the columns for any variable which is unable to fit in the specified number of columns. By this means a number of potential errors in formatting new (transformed) variables were avoided. Finally, entire data sets were written in hard copy and examined for missing or inappropriate values on many occasions throughout data transformation, file matching and file updating phases of this project. Inconsistencies were examined and errors in programming were identified and corrected whenever possible.

Rationales for Selection of Statistical Techniques, Measures and Tests.

Dobson (1983) and Lee (1980) both stress that Cox's (1970) linear logistic regression method is the most powerful statistical analysis which can be appropriately used when dichotomous criteria are being predicted. In the present study, this is the case for the parole recidivism measures 'arrest for violent felony' (coded Yes/No) and 'arrest for general felony' (coded Yes/No). Lee (1980) notes that treating a dichotomous criterion measure as if it is quantitative for use of the ordinary linear regression technique is inappropriate because (a) the values of the criterion measure (Y_i's) are not normally distributed and therefore no method of estimation that is linear in the Y_i's will be fully efficient, and (b) it is possible for the least-squares estimates obtained from the model to lead to a fitted value that does not satisfy the condition $0 \leq P_i \leq 1$, where P_i is the sum of all the predictor measures in the regression equation, each multiplied by its respective coefficient.

Another method of statistical analysis which is a potential competitor when the criterion variable is dichotomous is linear discriminant analysis; however, Press and

Wilson (1978) cite results of research indicating that logistic regression gives a higher correct classification rate when (a) the assumption of normally distributed predictor measures is violated, (b) covariance matrices are not identical for predictor measures, or (c) one or more predictor measures are qualitative or measured in nominal (especially dichotomous) or ordinal scales. As mentioned at the outset of this section of the chapter, each of these situations exists in the present study. It was therefore concluded that stepwise logistic regression was the best technique for use in prediction of the dichotomous criterion measures used.

No distributional assumptions are required for logistic regression; however, as Allen and Yen (1979) note, it is assumed that the probability distribution of a predictive "hit" or "success" across the range of values for predictor measures is a cumulative normal or logistic function. Program PLR in BMDP (BioMedical Data analysis software: P-series), developed by Laszlo Engelman (1983) provides three goodness-of-fit chi-square statistics to assist the researcher in determining the fit of a given data set to the linear logistic model. First, the standard goodness-of-fit chi-square can be used to test the hypothesis that the model at that step fits the data adequately. This is computed from the observed versus predicted frequencies at each cell in the data. Misleading results can occur, however, when cell frequencies are small (i.e., less than 5). This was the case for a number of logistic regressions in this study. Secondly, the 'Hosmer' goodness-of-fit test compares the observed and predicted frequencies of ten cells, which are defined by the predicted values. A small p-value means that the predicted values do not fit the data. Finally, the 'C.C. Brown' goodness-of-fit test compares the fit of the data to the logistic model with the fit obtained by some alternate member of the family of models referred to in Engelman (1983). A small p-value (in this case, less than .05) usually indicates that the logistic model is not the most appropriate for the data; however, it may simply indicate lack of a good fit to any of the models included in the family examined (i.e., lack of relationship between predictor and criterion measures).

Results of these goodness-of-fit tests are not necessarily conclusive concerning the appropriateness of application for a given statistical method. Instead, there is confounding between measurement of predictive accuracy and measurement concerning the appropriateness of the statistical model employed. The values of these measures are reported in Chapter V (Results).

Of the three goodness-of-fit tests, the 'C.C. Brown' test is the most likely to indicate the extent to which the logistic model is appropriate for the data (i.e., the least likely to be confounded with measurement of predictive accuracy); however, since it involves only comparison with a small family of alternate models (as do most such measures), the value of the statistic cannot be taken as conclusive for all possible models. Another point worthy of mention concerning this statistic is that for each logistic regression at "step 0" (entry of constant only) the value of the 'C.C. Brown' test is 0.0, with 0 degrees of freedom, resulting in a p-value of 1.00. Hence, when one is seeking to determine whether or not the logistic model is appropriate for determining the observed level of statistical significance for bivariate relationships between predictor and criterion measures, the 'C.C. Brown' goodness-of-fit test is of limited benefit.

Analysis of Relationships Between Individual Measures, Including Multivariate Associations.

Analyses described in this subsection include univariate descriptive statistics and measures of both bivariate and multivariate relationships between predictor and criterion measures. Univariate descriptive statistics reported include measures of central tendency and dispersion, and for non-continuous predictor and criterion measures, frequencies with percentages.

Assessments of bivariate relationships were determined using logistic regression. Statistics were computed for both subsamples. In order to determine the directionality of associations, operational measures of predictor variables had to be "forced" to enter regression equations on separate runs by lowering criteria to enter. Indicators of directionality are not provided in the BMDP:LR program until after the first step. Details of the computerized analyses used for stepwise logistic regression are described in program PLR in the BMDP Statistical Software manual (Engelman, 1983). This program includes a hierarchical rule for entry and removal of predictors and for this study the option allowing only one term to be entered or removed with each step was selected. With this option a term can be entered if all its lower-order interactions are already in the model, or a term can be removed if none of its higher-order interactions are already in the model.

In Engelman's (1983) computer analysis, regression coefficients are estimated by the maximum likelihood method and the user has the option of basing selection of variables for entry or removal on either the maximum likelihood ratio or an approximate asymptotic covariance estimate. Since the latter selection procedure is considerably more efficient and less expensive, it was selected for use in the study. Stepping of terms is controlled by entry and removal limits. P-values less then .05 to enter and greater than .07 to remove were selected for the study. The default value was used for the tolerance limit in the inversion of the cross product of partial derivatives matrix (.0001). Default values were also specified for the convergence criterion of the likelihood function (.000001), the maximum number of iterations to maximize the likelihood function (10) and the maximum number of step halvings allowed (5).

One of the major features of the stepwise logistic regression program is that predictor measures can be either categorical or continuous. The program generates "design variables" for the categorical measures and their interactions. For a categorical measure with three categories, two such design variables are generated. The design variables for each categorical measure (or interaction term) are considered as a set.

When developing the logistic regression models, separate regressions were performed for the two criterion measures (violent and general felony arrests on parole) alternating the two subsamples as construction and cross-validation samples.

Analysis of the Predictive Accuracy of the Logistic Regression Models Developed in the Study.

The logistic models were applied to cross-validation samples of either 317 or 323 cases, depending on which subsample was treated as the construction sample in each analysis. Engelman's (1983) program calculates the loss function using weights assigned to predictive outcomes. Figure 4.2 is an illustration of predictive outcomes with assignment of default weights. Predictive loss, using default values, would be calculated as 0.0(A) - 1.0(B) - 1.0(C) + 0.0(D). The cut-point for predicted probabilities which minimizes the loss function for the construction sample is applied to the cross-validation sample and predictive outcomes are reported. The BMPD:LR program reports outcomes for 49 cut-points evenly distributed

Observed Outcome		Predicted Outcome: Arrest	Predicted Outcome: No Arrest
	Arrest	True Positive Predictions A Weighted 0.0 (default)	False Negative Predictions B Weighted -1.0 (default)
	No Arrest	False Positive Predictions C Weighted -1.0 (default)	True Negative Predictions D Weighted 0.0 (default)

<u>Figure 4.1</u>. Illustration of weightings for predictive outcomes to calculate predictive loss.

between predicted probabilites of 0.025 and 0.825 in summary tables for each regression but since these are not directly relevant to analysis of predictive accuracy they are not included in this report.

The resulting 2 by 2 matrices from the analyses of predictive outcomes for logistic regressions were then subjected to manual calculations of Mean Cost Rating (MCR) and Improvement Over Chance (IOC). These statistics were described in Chapter III, but will be applied to one of the 2 by 2 matrices from the study at this point, to serve as an example. Figure 4.2 is an example of a parole risk prediction-by-outcome matrix. Values from this example will be used in the following sets of calculations, for MCR and IOC, respectively.

For the calculation of MCR, according to the method outlined by Inciardi, Babst and Koval (1973), the first step is to order the categories of the risk prediction scale according to increasing proportions (within each category) of favorable outcomes. In the example from the study, favorable outcomes are parolees who were not arrested for violent felonies during the 2 1/2 year follow-up. Table 4.7 includes these and other values, calculated from the example matrix. Column 1 in the table lists the number of cases in each risk category (from column totals), column 2 is a list of the percentage of favourable and unfavourable outcomes, respectively. The proportions of total favourable and unfavourable outcomes are listed in columns 5 and 6, 1984 Version of Iowa Model - Predicted Risk

Parole Outcome		Good Risk or Better		Fair Risk or Poorer		
No Arrest for Violent Felony		Count	106	Count	181	287
		Row %	36.9	Row %	63.1	89.4%
		Column %	92.2	Column %	87.9	
		Total %	33.0	Total %	56.4	
		(Valid Negatives)				
Arrest for Violent Felony		Count	9	Count	25	34
		Row %	26.5	Row %	73.5	10.6% (Base Rate)
		Column %	7.8	Column %	12.1	
		Total %	2.8	Total %	7.8	
				(Valid Positives)		
	Column Total		115 35.8%		206 64.2%	321 100%

Figure 4.2. Example of 2x2 prediction-outcome matrix.

Table 4.7. Calculations using values from example 2x2 prediction—outcome matrix for computing MCR.

	1	2	3	4	5	6	7	8	9	10
			Outcome		Proportion of Total		Cumulative Proportion			
Collapsed 1984 Iowa Violence Risk Categories	No. of Cases	% Favourable outcome in each category	No. of Favorable	No. of Not Favorable	Favorable	Not Favorable	C_i (Cost) Favorable	U_i (Utility) Not Favorable	$C_i U_{i-1}$	$U_i C_{i-1}$
							.63	.74	0	0
Fair risk or worse	206	87.9%	181	25	.63	.74	1.00	1.00	.74	.63
Good risk or better	115	92.2%	106	9	.37	.26	-	-	.74	.63
Total	321	-	287	34	1.00	1.00				

MCR = .74 - .63 = .11

respectively. Cumulative proportions are provided in columns 7 and 8. Finally, column 9 represents C_i or "cost" (column 7) multiplied by U_{i-1} or "utility" (Column 8). The "-1" in the subsript denotes the previous row in a column; for example, the first value in column 9 is computed by multiplying the value in the first row of column 7 (C_i), which is .63, by the value in the previous row for column 8 (U_i). Since there is no previous row in column 8, .63 is multiplied by 0 and the result is zero. The value in the second row of column 9 (.74) is computed by multiplying the value in the second row of column 7 (1.00) by the value in the previous row from column 8 (.74). Column 10 represents U_i (column 8) multiplied by C_{i-1} (column 7). C_{i-1} is derived by the same method as U_{i-1} for column 9. The sum of the values in column 10 is then subtracted from the sum of the values in column 9, to arrive at the Mean Cost Rating for this example, which is .11.

Improvement Over Chance (IOC), a measure recommended by Loeber and Dishion (1983) for assessing the extent to which predictive outcomes demonstrate improvement over chance alone, is then applied to values from the example in Figure 4.3. The first step in calculating IOC is to determine the proportions of cases which would be valid negatives and valid positives by chance alone, using marginal proportions for these cells. The expected proportion of cases which would constitute valid negative predictions by chance alone would be: 115/321 times 287/321 = .320. The expected proportion of valid positives would be 334/321 times 206/321 = .067. Together, the expected (by chance) valid predictions would total 38.7 percent for the example in Figure 4.3. Adding the 'percent of total' values together for observed valid positives and valid negatives, 40.8 percent of the predictions are accurate. Improvement Over Chance is the difference between 40.8 percent and 38.7 percent. Hence, IOC equals 2.1 percent.

These calculations for MCR and IOC were performed on predictive outcomes of the logistic regressions for both construction and cross-validation samples involving the dichotomous criteria of arrests for violent and general felonies while on parole.

Chapter Summary

In this chapter descriptive statistics have been provided for two subsamples, each comprising approximately half of the 640 cases used. Operational measures have been listed and described for each of the five major variables in the study, including: (a) criminal history, (b) current offense, (c) substance abuse history, (d) age, and (e) recidivism on parole. Each of these variables has been incorporated in testable hypotheses. Four of these hypotheses require investigation of bivariate relationships between predictor and criterion measures for both subsamples (using stepwise logistic regression) and the remaining two require calculations of statistics to assess the predictive accuracy of multivariate actuarial risk prediction models developed using stepwise logistic regression. These prediction models, or equations, are subjected to cross-validation using case records of parolees not included in construction samples for each regression. The first three equations were constructed on subsample I (N=304) and cross-validated on subsample II (N=308). The second set of three equations was constructed using subsample II, and cross-validated on subsample I. One regression from each set of three was developed to predict arrest for violent felony and one from each set was developed to predict arrest for general (violent or nonviolent) felony. The remaining two equations were constructed to predict arrest for general felony, but marital status and race were excluded from consideration as predictors.

Mean Cost Rating (MCR) and Improvement Over Chance (IOC) statistics were used to measure the accuracy of predictions generated, for both construction and cross-validation samples.

Since the study involves the use of offender file data which was previously collected, a good deal of detailed information is provided concerning preliminary coding, recoding and analysis of data. Rationales are provided for selection of statistical methods and tests used.

CHAPTER V

Results

A review of the literature pertaining to the variables and testable hypotheses in the study was provided in Chapters II and III. For the sake of consistency, results are presented according to the same order of variables given in these literature review chapters, which corresponds to the order of testable hypotheses for the study. Chapter V is organized in five sections: (a) univariate descriptive statistics, (b) bivariate relationship statistics, (c) development of logistic regression models, (d) analyses of the predictive accuracy of the logistic regression models, and (e) the chapter summary.

Univariate Descriptive Statistics

The operational measures for each variable are listed separately. Means and standard deviations are given for continuous measures and frequencies with percentages are provided for categorical measures.

Criminal History

Descriptive statistics for operational measures of criminal history are provided in Tables 5.1 and 5.2. Although these tables are essentially self-explanatory, a number of points seemed worthy of comment. First, only

Table 5.1. Descriptive statistics for operational measures of criminal history (Subsample I - 317 cases).

Measure No.	Name of Measure & Category Labels	No. of Valid Cases	Continuous Measures: Mean	Continuous Measures: Standard Deviation	Continuous Measures: (Range)	Categorical Measures: Frequency	Categorical Measures: Valid Percent
1	Number of years of street time since 14 yrs. of age	316	10.15	6.65	(0-47)		
2	Number of prior arrests	316	6.16	6.75	(0-53)		
3	Number of prior probations	316	1.31	1.29	(0-6)		
4	Number of prior adult jail terms	316	1.70	4.14	(0-50)		
5	Number of prior juvenile commitments	316	0.27	0.68	(0-6)		
6	Number of prior adult commitments	316	0.62	0.98	(0-5)		
7	Total number of violent felony charges	304	1.20	1.28	(0-7)		
8	Number of violent felony charges in last 12 months of street time	304	0.70	0.72	(0-4)		
9	Number of violent felony charges in last 24 months of street time	304	0.80	0.82	(0-4)		
10	Number of violent felony charges in last 36 months of street time	304	0.88	0.92	(0-5)		
11	Number of violent felony charges in last 5 years of street time	304	0.95	1.02	(0-7)		
12	Total number of nonviolent felony charges	304	3.66	3.77	(0-28)		
13	Number of nonviolent felony charges in last 12 months of street time	304	1.37	1.67	(0-11)		
14	Number of nonviolent felony charges in last 24 months of street time	304	1.79	2.16	(0-15)		
15	Number of nonviolent felony charges in last 36 months of street time	304	2.17	2.39	(0-15)		
16	Number of nonviolent felony charges in last 5 years of street time	304	2.56	2.62	(0-15)		
17	Evidence of juvenile felony: No					218	69.0
	: Yes					98	31.0
	: Missing					1	-
18	Property (nonviolent) disposition greater than 1 year: No					156	44.4
	: Yes					160	50.6
	: Missing					1	-
19	Person (violent) disposition greater than 1 year: No					249	78.8
	: Yes					67	21.2
	: Missing					1	-
20	Felony History: No prior arrest for felony as juvenile or adult					46	14.6
	: Prior arrest for felony					270	85.4
	: Missing					1	-
21	Multiple different charges with single arrest: No					243	79.9
	: Yes					61	20.1
	: Missing					13	-
22	Number of major non-bondable misconducts: None					197	62.3
	: One					67	21.2
	: Two or more					52	16.50
	: Missing					1	-
23	Proportion of years of street time to years of calendar time since 14 years of age	316	67.65	17.94	(0-100)		

Table 5.2. Descriptive statistics for operational measures of criminal history (Subsample II - 323 cases).

Measure No.	Name of Measure & Category Labels	Continuous Measures: No. of Valid Cases	Mean	Standard Deviation	(Range)	Categorical Measures: Frequency	Valid Percent
1	Number of years of street time since 14 yrs. of age	321	10.01	7.14	(0-48)		
2	Number of prior arrests	321	6.30	5.75	(0-40)		
3	Number of prior probations	321	1.39	1.22	(0-7)		
4	Number of prior adult jail terms	321	1.46	2.27	(0-19)		
5	Number of prior juvenile commitments	321	0.34	0.78	(0-6)		
6	Number of prior adult commitments	321	0.59	0.97	(0-5)		
7	Total number of violent felony charges	313	1.28	1.48	(0-7)		
8	Number of violent felony charges in last 12 months of street time	313	0.64	0.82	(0-6)		
9	Number of violent felony charges in last 24 months of street time	313	0.78	0.99	(0-6)		
10	Number of violent felony charges in last 36 months of street time	313	0.87	1.10	(0-6)		
11	Number of violent felony charges in last 5 years of street time	313	0.97	1.20	(0-7)		
12	Total number of nonviolent felony charges	312	3.64	3.17	(0-25)		
13	Number of nonviolent felony charges in last 12 months of street time	312	1.49	1.49	(0-11)		
14	Number of nonviolent felony charges in last 24 months of street time	312	1.93	1.77	(0-11)		
15	Number of nonviolent felony charges in last 36 months of street time	312	2.27	1.98	(0-11)		
16	Number of nonviolent felony charges in last 5 years of street time	312	2.78	2.42	(0-19)		
17	Evidence of juvenile felony: No					209	65.1
	: Yes					112	33.9
	: Missing					2	-
18	Property (nonviolent) disposition greater than 1 year: No					142	44.2
	: Yes					179	55.8
	: Missing					2	-
19	Person (violent) disposition greater than 1 year: No					245	76.3
	: Yes					76	23.7
	: Missing					2	-
20	Felony History: No prior arrest for felony as juvenile or adult					36	11.2
	: Prior arrest for felony					285	88.8
	: Missing					2	-
21	Multiple different charges with single arrest: No					242	77.6
	: Yes					70	22.4
	: Missing					11	-
22	Number of major non-bondable misconducts: None					215	67.0
	: One					63	19.6
	: Two or more					43	13.4
	: Missing					2	-
23	Proportion of years of street time to years of calendar time since 14 years of age	321	66.43	17.94	(0-100)		

about 30 percent of parolees had evidence in their files of arrests or charges for felonies as juveniles but over 85 percent had been arrested for a felony previously when adult offenses (prior to the current offense) were included. This finding indicates that the majority of offenders in the study began their felonious criminal activities after 18 years of age and established recidivistic patterns of behavior when released as adults. Other indicators of this habitual criminality include the numbers of prior arrests and nonviolent felony charges (means of approximately 6.0 and 3.6, respectively).

Secondly, while half of the parolees have records of dispositions greater than one year for property (nonviolent) crimes, only one-fifth have dispositions greater than one year for person (violent) crimes.

Current Offense

Descriptive statistics for operational measures of current offense are provided in Tables 5.3 and 5.4. Again, although the tables are basically self-explanatory, two highlights seem worth mentioning. First, the most common current offenses in the Michigan categorization are burglary, larceny and armed robbery, accounting for approximately one-fifth of all current offenses each. Secondly, the small percentage of offenders currently serving a sentence for escape or jailbreak (approximately 3 percent) severely limits the usefulness of this operational measure as a predictor of recidivism on parole.

Table 5.3. Descriptive statistics for operational measures of current offense (subsample I - 317 cases).

Measure No.	Name of Measure & Category Labels		Frequency	Valid Percent
1	Current offense (Michigan coding):	Homicide	21	6.6
		: Attempted murder	0	0.0
		: Assault with intent to murder	16	5.1
		: CSC, rape	17	5.4
		: Attempt to Asslt. to CSC, rape	3	0.9
		: Abduction, kidnapping	0	0.0
		: Robbery armed	61	19.3
		: Robbery unarmed	6	1.9
		: Attempted robbery	1	0.3
		: Assault with intent to rob	13	4.1
		: Other assaults (felonious, asslt. to maim, etc.)	5	1.6
		: Sodomy	1	0.3
		: Gross indecency	0	0.0
		: Children: Torture, cruelty, expose	0	0.0
		: Indecent liberties with child	0	0.0
		: Extortion	0	0.0
		: Larceny from person (assaultive)	10	3.2
		: Larceny from person (non-assaultive)	3	0.9
		: Arson - dwelling only	0	0.0
		: Arson - building	0	0.0
		: Aggravated burglary	1	0.3
		: Burglary	50	15.8
		: Larceny (Includes larceny auto)	47	14.9
		: Auto theft	4	1.3
		: Forgery - Uttering & Publishing	13	4.1
		: Embezzlement	1	0.3
		: Bad checks	0	0.0
		: Malicious destruction	0	0.0
		: Drugs	26	8.2
		: Alcohol related	1	0.3
		: Sex offenses (other)	0	0.0
		: Children offenses (other)	0	0.0
		: Negligent homicide	2	0.6
		: Other offenses	14	4.4
		: Missing	1	-
2	Serving on current escape or jail break sentence	: No	305	96.5
		: Yes	11	3.5
		: Missing	1	-

Table 5.4. Descriptive statistics for operational measures of current offense (subsample II - 323 cases).

Measure No.	Name of Measure & Category Labels		Frequency	Valid Percent
1	Current offense (Michigan coding):	Homicide	13	4.0
	:	Attempted murder	0	0.0
	:	Assault with intent to murder	4	1.2
	:	CSC, rape	10	3.1
	:	Attempt to Asslt. to CSC, rape	5	1.6
	:	Abduction, kidnapping	1	.3
	:	Robbery armed	41	12.8
	:	Robbery unarmed	8	2.5
	:	Attempted robbery	1	.3
	:	Assault with intent to rob	19	5.9
	:	Other assaults (felonious, asslt. to maim, etc.)	14	4.4
	:	Sodomy	0	0.0
	:	Gross indecency	0	0.0
	:	Children: Torture, cruelty, expose	0	0.0
	:	Indecent liberties with child	0	0.0
	:	Extortion	1	.3
	:	Larceny from person (assaultive)	1	.3
	:	Larceny from person (non-assaultive)	2	.6
	:	Arson - dwelling only	4	1.2
	:	Arson - building	0	0.0
	:	Aggravated burglary	2	.6
	:	Burglary	73	22.7
	:	Larceny (Includes larceny auto)	38	11.8
	:	Auto theft	7	2.2
	:	Forgery - Uttering & Publishing	13	4.0
	:	Embezzlement	0	0.0
	:	Bad checks	3	.9
	:	Malicious destruction	0	0.0
	:	Drugs	47	14.6
	:	Alcohol related	0	0.0
	:	Sex offenses (other)	0	0.0
	:	Children offenses (other)	0	0.0
	:	Negligent homicide	0	0.0
	:	Other offenses	14	4.4
	:	Missing	2	-
2	Serving on current escape or jail break sentence	: No	312	97.2
	:	Yes	9	2.8
	:	Missing	2	-

Substance Abuse History

Descriptive statistics for operational measures of substance abuse history are provided in Tables 5.5 and 5.6. Almost one fourth of all parolees in the study reportedly had no indication of substance abuse in their histories. Of those for whom substance abuse was reported, the most serious forms of abuse indicated by the great majority of parolees were opiate addiction and heavy hallucinogen use, together accounting for approximately 55 percent of parolees in the study. In contrast, with only two to three percent of parolees reportedly using the hardest chemicals (PCP or sniffing volatile substances) the usefulness of this category of substance abuse as a separate measure (number 3) is severely limited for prediction of recidivism. Finally, it should be noted that measures 2 through 6 are all collapsed versions of measure number 1.

Age

Descriptive statistics for operational measures of age are provide in Tables 5.7 and 5.8. Although means and standard deviations for these measures were given in the methods chapter, they are provided at this point for ease of reference to maintain consistency in presentation of results regarding operational measures for variables in the study. Across the two subsamples, age at first criminal arrest ranged from 7 to 39 years with a mean of approximately 18 years. Age at time of parole ranged from 18 years to 70 years across the two subsamples, with a mean of

Table 5.5. Descriptive statistics for operational measures of substance abuse history (subsample I - 317 cases).

Measure Number	Name of Measure & Category Labels	Frequency	Valid Percent
1	Substance Abuse Scale		
	: PCP use	4	1.3
	: Sniffing volatile substance	2	0.6
	: Opiate addiction	95	30.1
	: Heavy hallucinogen use	70	22.2
	: Drug problem	2	0.6
	: Opiate or hallucinogen use	22	7.0
	: Alcohol problem	43	13.6
	: No history as above	78	24.7
	: Missing	1	-
2	Collapsed Substance Abuse Scale		
	: Hardest chemicals used	6	1.9
	: Problem opiate/hallucinogen use	165	52.2
	: Some abuse of chemicals	24	7.6
	: Alcohol problem only	43	13.6
	: No history as above	78	24.7
	: Missing	1	-
3	PCP or sniffing volatile substance: No	310	98.1
	: Yes	6	1.9
	: Missing	1	-
4	Serious problem use of chemical substances : No	145	45.9
	: Yes	171	54.1
	: Missing	1	-
5	Any prior abuse of some form of chemical substance : No	121	38.3
	: Yes	195	61.7
	: Missing	1	-
6	Prior abuse of some substance: No	78	24.7
	: Yes	238	75.3
	: Missing	1	-

Table 5.6. Descriptive statistics for operational measures of substance abuse history (subsample II - 323 cases).

Measure Number	Name of Measure & Category Labels	Frequency	Valid Percent
1	Substance Abuse Scale		
	: PCP use	8	2.5
	: Sniffing volatile substance	2	0.6
	: Opiate addiction	118	36.8
	: Heavy hallucinogen use	73	22.7
	: Drug problem	2	0.6
	: Opiate or hallucinogen use	14	4.4
	: Alcohol problem	37	11.5
	: No history as above	67	20.9
	: Missing	2	-
2	Collapsed Substance Abuse Scale		
	: Hardest chemicals used	10	3.1
	: Problem opiate/hallucinogen use	191	59.5
	: Some abuse of chemicals	16	5.0
	: Alcohol problem only	37	11.5
	: No history as above	67	20.9
	: Missing	2	-
3	PCP or sniffing volatile substance: No	311	96.9
	: Yes	10	3.1
	: Missing	2	-
4	Serious problem use of chemical substances : No	120	37.4
	: Yes	201	62.6
	: Missing	2	-
5	Any prior abuse of some form of chemical substance : No	104	32.4
	: Yes	217	67.6
	: Missing	2	-
6	Prior abuse of some substance: No	67	20.9
	: Yes	254	79.1
	: Missing	2	-

Table 5.7. Descriptive statistics for operational measures of age (subsample I - 317 cases).

Measure Number	Name of Measure	No. of Valid Cases	Mean	Standard Deviation	(Range)
1	Age at time of parole	316	28.78	7.85	(18-70)
2	Age at time of first criminal arrest	315	18.00	4.63	(8-38)

Table 5.8. Descriptive statistics for operational measures of age (subsample II - 323 cases).

Measure Number	Name of Measure	No. of Valid Cases	Mean	Standard Deviation	(Range)
1	Age at time of parole	321	28.71	8.07	(19-63)
2	Age at time of first criminal arrest	320	17.31	4.39	(7-39)

approximately 29 years.

Recidivism on Parole

Descriptive statistics for operational measures of recidivism on parole are provided in Tables 5.9 and 5.10. The records of almost 60 percent of the parolees studied indicated no arrests for felonies while on parole. Over 40 percent of parolees were arrested for a general (either violent or nonviolent) felony while on parole (base rate for violent felony arrest alone is approximately 12 percent).

Bivariate Relationship Statistics

This section of the chapter is a presentation of results pertaining to relationships between individual operational measures of predictor variables and operational measures of the criterion variable. Findings are presented according to the order of testable hypotheses to which they correspond.

Criminal History

The first hypothesis was that operational measures of criminal history would be related to measures of felonious recidivism on parole. This generic hypothesis was expanded into two more refined, testable hypotheses, each pertaining to relationships of predictor measures with a different criterion measure. It is around such secondary or sub-hypotheses that this, and the following subsections of this chapter, are arranged.

Table 5.9. Descriptive statistics for operational measures of recidivism on parole (subsample I - 317 cases).

Measure Number	Name of Measure and Category Labels		Frequency	Valid Percent
1	Arrest for violent felony on parole	: No	274	86.7
		: Yes	42	13.3
		: Missing	1	-
2	Arrest for general felony on parole	: No	177	56.0
		: Yes	139	44.0
		: Missing	1	-

Table 5.10. Descriptive statistics for operational measures of recidivism on parole (subsample II - 323 cases).

Measure Number	Name of Measure and Category Labels		Frequency	Valid Percent
1	Arrest for violent felony on parole	: No	287	89.4
		: Yes	34	10.6
		: Missing	2	-
2	Arrest for general felony on parole	: No	190	59.2
		: Yes	131	40.8
		: Missing	2	-

1(a) Relationships between operational measures of criminal history and the criterion measure 'arrest for violent felony on parole.' Investigation of relationships between each predictor and criterion measure requires individual hypotheses. Inferential statistics are used to test the extent to which observed values deviate from those which would be expected by chance if each null hypothesis were true.

Since the criterion measure is dichotomous for the first hypothesis, logistic regression was used to determine whether or not statistically significant relationships existed with each predictor. Results are presented in Table 5.11.

For subsample I (N=304 cases) two operational measures of criminal history were significantly ($p < .05$) related to the criterion measure 'arrest for violent felony,' including 'number of years of street time since 14 years of age' and 'person (violent) disposition greater than one year.' For subsample II (N=308) four measures of criminal history were significantly related to the criterion measure 'arrest for violent felony,' including: 'total number of violent felony charges,' 'number of violent felony charges in last 36 months of street time,' 'number of violent felony charges in last 5 years of street time,' and 'proportion of years of street time to calendar time since 14 years of age.' Interestingly, no operational measure of criminal history

Table 5.11. Relationship between operational measures of criminal history and the criterion measure "arrest for violent felony on parole".

Measure No.	Name of Measure	Subsample I (N=304*; df=1/302**) F to Enter	Subsample I P-Value	Subsample II (N=308*; df=1/306**) F to Enter	Subsample II P-Value
1	Number of years of street time since 14 yrs. of age	3.95	.0479	1.72	.1903
2	Number of prior arrests	0.00	.9672	0.97	.3266
3	Number of prior probations	0.42	.5190	0.03	.8586
4	Number of prior adult jail terms	0.00	.9824	0.05	.8216
5	Number of prior juvenile commitments	0.46	.4968	2.87	.0914
6	Number of prior adult commitments	0.00	.9752	0.15	.6965
7	Total number of violent felony charges	3.67	.0562	4.12	.0433
8	Number of violent felony charges in last 12 months of street time	0.17	.6788	2.34	.1268
9	Number of violent felony charges in last 24 months of street time	1.61	.2054	1.16	.2821
10	Number of violent felony charges in last 36 months of street time	1.74	.1885	4.26	.0398
11	Number of violent felony charges in last 5 years of street time	3.53	.0614	6.35	.0122
12	Total number of nonviolent felony charges	1.13	.2876	0.03	.8739
13	Number of nonviolent felony charges in last 12 months of street time	0.29	.5899	0.15	.6991
14	Number of nonviolent felony charges in last 24 months of street time	0.00	.9876	0.10	.7495
15	Number of nonviolent felony charges in last 36 months of street time	0.08	.7827	0.18	.6699
16	Number of nonviolent felony charges in last 5 years of street time	0.23	.6311	1.05	.3056
17	Evidence of juvenile felony	3.63	.0579	0.18	.6704
18	Property (nonviolent) disposition greater than 1 year	0.14	.7073	0.58	.4465
19	Person (violent) disposition greater than 1 year	4.02	.0457	0.00	.9876
20	Felony History	0.21	.6491	1.68	.1958
21	Multiple different charges with single arrest	0.01	.9432	0.20	.6578
22	Number of major non-bondable misconducts	1.42	.2442	2.22	.1104
23	Proportion of years of street time to years of calendar time since 14 years of age	1.04	.3082	4.92	.0273

* N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

** With the exception of 'number of major non-bondable misconducts', for which degrees of freedom are 2 and 301 for subsample I, and 2 and 305 For subsample II.

was found to be significantly related to the criterion measure 'arrest for violent felony' across both subsamples.

1(b) Relationships between operational measures of criminal history and the criterion measure 'arrest for general felony while on parole.' Results pertaining to this hypothesis are presented in Table 5.12.

For subsample I, 12 of the 23 operational measures of criminal history were significantly related to the criterion measure 'arrest for general felony,' including both street time measures (1 and 23), all five prior nonviolent felony charge measures (12 through 16), 'number of prior juvenile commitments,' 'number of violent felony charges in last 12 months of street time,' 'evidence of a juvenile felony,' 'property (nonviolent) disposition greater than 1 year' and 'felony history.' For subsample II, 10 of the 23 operational measures of criminal history were significantly related to the criterion measure 'arrest for general felony,' including: both street time measures (1 and 23), four of the five prior nonviolent felony charge measures (13 through 16), 'number of prior arrests,' 'number of prior juvenile commitments,' 'evidence of juvenile felony' and 'number of major non-bondable misconducts.'

Across both subsamples, 8 of the 23 operational measures of criminal history were significantly related to the criterion measure 'arrest for general felony,' including: both street time measures (1 and 23), four of the five prior nonviolent felony charge measures (13 through

Table 5.12. Relationship between operational measures of criminal history and the criterion measure "arrest for general felony on parole".

Measure No.	Name of Measure	Subsample I (N=304*; df=1/302**)		Subsample II (N=308*; df=1/306**)	
		F to Enter	P-Value	F to Enter	P-Value
1	Number of years of street time since 14 yrs. of age	17.16	.0000	18.57	.0000
2	Number of prior arrests	1.57	.2116	8.66	.0035
3	Number of prior probations	1.19	.2771	2.56	.1106
4	Number of prior adult jail terms	0.05	.8150	0.23	.6356
5	Number of prior juvenile commitments	8.69	.0035	11.43	.0008
6	Number of prior adult commitments	2.17	.1421	0.41	.5239
7	Total number of violent felony charges	0.53	.4672	1.35	.2462
8	Number of violent felony charges in last 12 months of street time	5.95	.0153	1.18	.2792
9	Number of violent felony charges in last 24 months of street time	2.42	.1212	1.09	.2971
10	Number of violent felony charges in last 36 months of street time	2.70	.1012	1.58	.2102
11	Number of violent felony charges in last 5 years of street time	0.43	.5146	2.47	.1168
12	Total number of nonviolent felony charges	9.22	.0026	2.78	.0964
13	Number of nonviolent felony charges in last 12 months of street time	17.96	.0000	5.63	.0183
14	Number of nonviolent felony charges in last 24 months of street time	20.55	.0000	6.72	.0100
15	Number of nonviolent felony charges in last 36 months of street time	19.79	.0000	6.57	.0108
16	Number of nonviolent felony charges in last 5 years of street time	18.43	.0000	10.58	.0013
17	Evidence of juvenile felony	6.23	.0131	19.24	.0000
18	Property (nonviolent) disposition greater than 1 year	6.58	.0108	0.52	.4734
19	Person (violent) disposition greater than 1 year	0.12	.7260	0.16	.6891
20	Felony History	4.08	.0443	3.78	.0527
21	Multiple different charges with single arrest	0.02	.8859	2.08	.1507
22	Number of major non-bondable misconducts	2.63	.0734	5.11	.0066
23	Proportion of years of street time to years of calendar time since 14 years of age	13.01	.0004	12.38	.0005

* N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

** With the exception of 'number of major non-bondable misconducts', for which degrees of freedom are 2 and 301 for subsample I, and 2 and 305 For subsample II.

16), 'number of prior juvenile commitments' and 'evidence of a juvenile felony.'

Current Offense

2(a) Relationships between operational measures of current offense and the criterion measure 'arrest for violent felony while on parole.' Results pertaining to this hypothesis are presented in Table 5.13. Neither of the operational measures of current offense is significantly related to the criterion measure for either subsample.

2(b) Relationships between operational measures of current offense and the criterion measure 'arrest for general felony while on parole.' Results are given in Table 5.14. Neither of the two measures was found to be significantly ($p < .05$) related to 'arrest for general felony on parole' for either subsample.

Substance Abuse

3(a) Relationships between operational measures of substance abuse history and the criterion measure 'arrest for violent felony while on parole'. Results pertaining to this hypothesis are presented in Table 5.15. None of the six operational measures of substance abuse history were significantly related with the criterion measure, for either sample.

3(b) Relationships between operational measures of substance abuse history and the criterion 'arrest for general felony while on parole'. Results regarding the hypothesis are provided in Table 5.16. None of the six operational

Table 5.13. Relationship between operational measures of current offense and the criterion measure 'arrest for violent felony on parole'.

Measure Number	Name of Measure	Subsample I (N=304*)			Subsample II (N=308*)		
		F to Enter	D.F.	P-Value	F to Enter	DF	P-Value
1	Current offense (Michigan coding)	0.94	25/278	.5524	1.03	25/282	.4339
2	Serving on current escape or jail break sentence	1.09	1/302	.2977	1.70	1/306	.1931

* N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

<u>Table 5.14</u>. Relationship between operational measures of current offense and the criterion measure 'arrest for general felony on parole'.

Measure Number	Name of Measure	Subsample I (N=304*)			Subsample II (N=308*)		
		F to Enter	D.F.	P-Value	F to Enter	DF	P-Value
1	Current offense (Michigan coding)	1.17	24/279	.2702	1.05	25/282	.4081
2	Serving on current escape or jail break sentence	1.28	1/302	.2592	2.99	1/306	.0850

* N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

Table 5.15. Relationship between operational measures of substance abuse history and the criterion measure 'arrest for violent felony on parole'.

Measure Number	Name of Measure	Subsample I (N=304*)			Subsample II (N=308*)		
		F to Enter	D.F.	P-Value	F to Enter	DF	P-Value
1	Substance Abuse Scale	0.81	7/296	.5800	0.40	7/300	.9038
2	Collapsed Substance Abuse Scale	0.45	4/299	.7698	0.47	4/303	.7599
3	PCP or sniffing volatile substance	0.98	1/302	.3225	0.07	1/306	.7872
4	Serious problem use of chemical substances	0.22	1/302	.6404	0.38	1/306	.5374
5	Any prior abuse of some form of chemical substance	0.51	1/302	.4747	0.78	1/306	.3771
6	Prior abuse of some substance	0.40	1/302	.5296	0.00	1/306	1.0000

* N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

Table 5.16. Relationship between operational measures of substance abuse history and the criterion measure 'arrest for general felony on parole'.

Measure Number	Name of Measure	Subsample I (N=304*)			Subsample II (N=308*)		
		F to Enter	D.F.	P-Value	F to Enter	DF	P-Value
1	Substance Abuse Scale	2.50	7/296	.0164	0.72	7/300	.6580
2	Collapsed Substance Abuse Scale	1.76	4/299	.1371	0.24	4/303	.9161
3	PCP or sniffing volatile substance	0.00	1/302	.9752	0.26	1/306	.6130
4	Serious problem use of chemical substances	5.15	1/302	.0240	0.04	1/306	.8342
5	Any prior abuse of some form of chemical substance	6.70	1/302	.0101	0.17	1/306	.6767
6	Prior abuse of some substance	2.51	1/302	.1142	0.02	1/306	.8942

* N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

measures of substance abuse history were significantly related to the criterion measure across both subsamples; however, for subsample I three operational measures were significantly related including the full substance abuse scale, 'serious problem use of chemical substances,' and 'any prior abuse of some form of chemical substance.' No operational measures of substance abuse history were significantly related to the criterion measure for subsample II.

Age

4(a) Relationships between operational measures of age and the criterion measure 'arrest for violent felony while on parole'. Results are provided in Table 5.17. One of the two measures, 'age at time of parole' was significantly negatively related with the criterion measure for subsample I, but neither measure was significantly related to the criterion across both subsamples. Direction of relationship is determined by coefficients given in results from the logistic regression procedures (see table 5.20).

4 (b) Relationships between operational measures of age and the criterion measure 'arrest for general felony while on parole'. Results concerning the hypothesis are given in Table 5.18, indicating significant relationships between both of these predictors and general felony arrest on parole for both subsamples. The signs of logistic regression coefficients (see Tables 5.20 and 5.22) indicate that relationships between these predictors and the criterion

<u>Table 5.17.</u> Relationship between operational measures of age and the criterion measure 'arrest for violent felony on parole'.

Measure Number	Name of Measure	Subsample I (N=304*; df=1/302) F to Enter	Subsample I P-Value	Subsample II (N=308*; df=1/306) F to Enter	Subsample II P-Value
1	Age at time of parole	4.41	.0366	0.37	.5431
2	Age at time of first criminal arrest	1.77	.1838	3.81	.0520

*N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

Table 5.18. Relationship between operational measures of age and the criterion measure 'arrest for general felony on parole'.

Measure Number	Name of Measure	Subsample I (N=304*; df=1/302)		Subsample II (N=308*; df=1/306)	
		F to Enter	P-Value	F to Enter	P-Value
1	Age at time of parole	11.51	.0008	11.83	.0007
2	Age at time of first criminal arrest	10.39	.0014	22.91	.0000

*N of cases varies from the totals available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.

measure are negative.

The predictor variables 'marital status' and 'race' are not included among the operational measures of criminal history, current offense, substance abuse history or age. Although no explicit hypotheses were included pertaining to these variables, they were considered for inclusion in the logistic regressions developed in the study because past research has so consistently reported strong associations between these characteristics and recidivism. Univariate descriptive statistics for marital status and race were displayed previously, in Chapter IV, relative to the demographic characteristics of the subsamples. Since these variables were considered for entry to the logistic regression equations, it seems reasonable to provide indicators of bivariate associations with recidivism. For subsample I (N=304), F to enter values are approximately 5.88 and 4.55, resulting in p-values of .0159 and .0338 (with 1 and 302 degrees of freedom), for race and marital status, respectively. For subsample II (N=308), F to enter values are approximately 8.14 and 17.15, resulting in p-values of .0046 and .0000 (with 1 and 306 degrees of freedom), for race and marital status respectively.

Development of Logistic Regression Models

A summary of stepwise results for three of the six logistic regressions is provided in Table 5.19. Coefficients with their standard errors at the final step in each regression are provided for each term in Table 5.20.

Table 5.19. Summary of stepwise results for three logistic regressions using subsample I for construction.

Regression Number	Name of Regression	Step No.	Term Entered	D.F.	Log Likelihood	Improvement Chi-Square	Improvement D.F.	Improvement P-Value	Standard Goodness of Fit Chi-Square	Standard Goodness of Fit D.F.	Standard Goodness of Fit P-Value	D.H. Hosmer Goodness of Fit Chi-Squ	D.H. Hosmer Goodness of Fit D.F.	D.H. Hosmer Goodness of Fit P-Value	C.C. Brown Goodness of Fit Chi-Square	C.C. Brown Goodness of Fit D.F.	C.C. Brown Goodness of Fit P-Value
1	Arrest for violent felony while on parole	0	Constant only		-102.293				204.587	302	1.000						
		1	Age at time of parole	1	-99.607	5.373	1	0.020	199.216	301	1.000	10.252	8	0.248	1.124	2	0.570
		2	Person (violent) disposition greater than 1 year	1	-96.176	6.862	1	0.009	192.354	300	1.000	5.399	8	0.714	1.428	2	0.490
2	Arrest for general felony while on parole	0	Constant only		-205.147				410.280	302	0.000						
		1	No. of nonviolent felony charges in last 24 months of street time	1	-195.295	19.704	1	0.000	390.579	301	0.000	12.492	8	0.131	1.633	2	0.442
		2	No. of years of street time since 14 years of age	1	-189.244	12.102	1	0.001	378.480	300	0.001	12.336	8	0.137	2.458	2	0.293
		3	Race	1	-184.157	10.174	1	0.001	368.306	299	0.004	6.514	8	0.590	4.407	2	0.110
		4	Substance abuse history	7	-176.398	15.519	7	0.030	352.789	293	0.009	7.018	8	0.535	2.377	2	0.305
		5	No. of violent felony charges in last 12 months of street time	1	-173.866	5.065	1	0.024	347.724	292	0.014	4.302	8	0.829	1.351	2	0.509
3	Arrest for general felony while on parole (excluding marital status and race as predictors)	0	Constant only		-205.147				410.280	302	0.000						
		1	Number of nonviolent felony charges in last 24 months of street time	1	-195.295	19.704	1	0.000	390.579	301	0.000	12.492	8	0.131	1.633	2	0.442
		2	Number of years of street time since 14 years of age	1	-189.244	12.102	1	0.001	378.480	300	0.001	12.336	8	0.137	2.458	2	0.293
		3	Substance abuse history	7	-179.786	18.917	7	0.008	359.565	294	0.005	7.134	8	0.522	0.466	2	0.793
		4	No. of violent felony charges in last 12 months of street time	1	-177.512	4.548	1	0.033	355.017	293	0.008	2.543	8	0.960	0.275	2	0.872

Table 5.20. Summary of stepwise logistic regressions, with coefficients for each term from the final step, using subsample I for construction.

Regression Number	Name of Regression	Step No.	Term Entered	D.F.	Statistics for Coefficients From Final Steps for Each Term: Coefficient	Standard Error	Coefficient/ S.E.
1	Arrest for violent felony while on parole	0	Constant only		0.6960	1.040	0.669
		1	Age at time of parole	1	-0.9563	0.383	-2.497
		2	Person (violent) disposition greater than than 1 year	1	0.5748	0.214	2.684
2	Arrest for general felony while on parole	0	Constant only		1.4439	0.883	1.635
		1	No. of nonviolent felony charges in last 24 months of street time	1	0.1903	0.779	2.443
		2	No. of years of street time since 14 years of age	1	-0.1121	0.288	-3.89
		3	Race	1	0.3800	0.143	2.668
		4	Substance abuse history	7			
			-no abuse/alcohol		-1.1478	0.947	-1.212
			-alcohol/some opiate or hallucinogen use		-0.9698	1.024	-0.947
			-some opiate or hallucinogen use/drug problem		-0.5235	1.691	-0.310
			-drug problem/heavy hallucinogen use		-1.4825	0.878	-1.689
			-heavy hallucinogen use/opiate addiction		-0.4914	0.865	-0.568
			-opiate addiction/sniffing volatile substance		8.0085	5.282	1.516
			-sniffing volatile substance/PCP use		-1.9430	0.0	0.0
		5	No. of violent felony charges in last 12 months of street time	1	-0.4063	0.189	-2.148
3	Arrest for general felony while on parole (excluding marital status and race as predictors)	0	Constant only		1.2363	1.451	0.852
		1	No. of nonviolent felony charges in last 24 months of street time	1	0.1920	0.775	2.477
		2	No. of years of street time since 14 years of age	1	-0.1006	0.277	-3.630
		3	Substance abuse history	7			
			-no abuse/alcohol		-1.1631	1.495	-0.778
			-alcohol/some opiate or hallucinogen use		-0.9391	1.546	-0.607
			-some opiate or hallucinogen use/ drug problem		-0.7821	0.0	0.0
			-drug problem/heavy hallucinogen use		-1.4416	1.455	-0.9907
			-heavy hallucinogen use/opiate addiction		-0.2424	1.449	-0.167
			-opiate addiction/sniffing volatile substance		7.6336	8.662	0.881
			-sniffing volatile substance/PCP use		-1.8372	1.651	-1.113
		4	No. of violent felony charges in last 12 months of street time	1	-0.3799	0.186	-2.044

The first stepwise logistic regression was developed for predicting the criterion measure 'arrest for violent felony while on parole.' The predictor 'age at time of parole' was the first to enter the equation, followed by 'person (violent) disposition greater than 1 year.' The small observed p-values for the chi-square improvement test ($p=.020$ and $p=.009$, for the first and second terms, respectively) indicate that both terms have considerable predictive value. The reported p-values of 1.000 for the standard chi-square goodness-of-fit test are misleading due to the large number of expected cell values less than five (limitation is mentioned in the BMDP documentation).

The relatively large observed p-values for the D.H. Hosmer and C.C. Brown goodness-of-fit tests indicate a reasonably good fit between the data and the logistic model. The fit of the model does not seriously come into question unless p-values less than .05 are observed. All p-values ranged from approximately .250 to .710. Finally, in Table 5.20, the negative coefficient for 'age at time of parole' may be noted, indicating an inverse relationship with recidivism.

The second logistic regression was developed to predict the criterion measure 'arrest for general felony while on parole.' Results of the stepwise procedure are presented in Table 5.19, with coefficients and standard errors of coefficients for each term at the final step listed in Table

5.20. The predictor measure 'number of nonviolent felony charges in last 24 months of street time' was the first to enter the equation, followed by 'number of years of street time since 14 years of age,' race, substance abuse history, and finally, 'number of violent felony charges in last 12 months of street time.' P-values for chi-square improvement and standard goodness-of-fit tests are considerably less than .05, indicating substantial predictive contributions to the equation and improvements in prediction with each successive term. P-values for D.H. Hosmer and C.C. Brown goodness-of-fit tests are all substantially greater than .05, indicating that the logistic model likely fits the data well. The negative coefficient for 'number of years of street time since 14 years of age' (see Table 5.20) was expected, but the negative coefficients for six of the seven design variables for substance abuse history and for 'number of violent felony charges in last 12 months of street time' are somewhat of a surprise. The fact that the design variables for substance abuse history entered the equation at all is not particularly surprising since this categorical measure was found to be significantly related to the criterion for subsample I. The negative values of coefficients, however, seem to defy explanation on any rational basis. Engelman (1983) noted that logistic regression coefficients divided by their respective standard errors generally had to exceed an absolute value of 2.00 in order to be practically useful for prediction. While for

each of the other predictors these absolute values exceeded 2.00, for all of the design variables pertaining to substance abuse history these absolute values were less than 2.00. Hence the real predictive contribution of the categorical variable substance abuse history is questionable.

The third logistic regression was constructed for the same criterion as the second ('arrest for general felony while on parole'), but the predictors of marital status and race were excluded from consideration. Not surprisingly, the terms that enter the equation (and the order of entry) are identical to those for the second regression, with the exclusion of race. Since results of these two regressions are so similar, all observations and comments made concerning the second regression apply equally well to this third regression.

The second series of three regressions was developed using subsample II for construction. Results of the stepwise procedures are reported in Table 5.21, with coefficients and standard errors of coefficients for each term at the final step listed in Table 5.22. Regression number four was constructed to predict the criterion measure 'arrest for violent felony while on parole.' The one measure selected for entry was 'number of violent felony charges in last five years of street time,' and once it entered no other term met the limit for entry ($p < .05$). A significant improvement in predictive accuracy occurred with

Table 5.21. Summary of stepwise results for three logistic regressions using subsample II for construction.

Regression Number	Name of Regression	Step No.	Term Entered	D.F.	Term Removed	Log Likelihood	Improvement Chi-Square	Improvement D.F.	Improvement P-Value	Standard Goodness of Fit Chi-Square	Standard Goodness of Fit D.F.	Standard Goodness of Fit P-Value	D.W. Hosmer Goodness of Fit Chi-Square	D.W. Hosmer Goodness of Fit D.F.	D.W. Hosmer Goodness of Fit P-Values	C.C. Brown Goodness of Fit Chi-Square	C.C. Brown Goodness of Fit D.F.	C.C. Brown Goodness of Fit P-Value
4	Arrest for violent felony while on parole	0	Constant only			-118.928				237.859	306	0.998						
		1	Number of violent charges in last 5 years of street time	1		-116.200	5.455	1	0.020	232.404	305	0.999	5.234	5	0.388	1.125	2	0.570
5	Arrest for general felony while on parole	0	Constant only			-210.880				421.739	306	0.000						
		1	Age at time of first criminal arrest	1		-198.899	23.962	1	0.000	397.789	305	0.000	9.196	8	0.326	0.561	2	0.756
		2	Marital status at time of current offense (0=Married; 1=Single)	1		-194.758	8.284	1	0.004	389.505	304	0.001	1.667	8	0.990	0.229	2	0.892
		3	Race (0=White; 1=Nonwhite)	1		-191.458	6.600	1	0.010	382.906	303	0.001	2.712	8	0.951	0.033	2	0.984
6	Arrest for general felony while on parole (excluding marital status and race as predictors)	0	Constant only			-210.880				421.739	306	0.000						
		1	Age at time of first criminal arrest	1		-198.899	23.962	1	0.000	397.789	305	0.000	9.196	8	0.326	0.561	2	0.756
		2	Number of years of street time since 14 years of age	1		-195.987	5.824	1	0.016	391.964	304	0.000	10.442	8	0.235	0.283	2	0.868
		3	Number of prior arrests	1		-191.364	9.246	1	0.002	382.718	303	0.001	6.079	8	0.638	0.409	2	0.815
		4		1	Age at time of first criminal arrest	-191.689	0.650	1	0.420	383.369	304	0.001	22.218	8	0.005	1.216	2	0.545
		5	Escape	1		-188.737	5.904	1	0.015	377.465	303	0.002	9.234	8	0.323	0.170	2	0.919

Table 5.22. Summary of stepwise logistic regressions, with coefficients for each term from the final step, using subsample II for construction.

Regression Number	Name of Regressions	Step No.	Term Entered	D.F.	Term Removed	Statistics for Coefficients From Final Steps for Each Term: Coefficient	Standard Error	Coefficient/ S.E.
4	Arrest for violent felony while on parole	0	Constant only			-2.2760	0.244	-9.313
		1	Number of violent charges in last 5 years of street time	1		-0.3451	0.143	2.406
5	Arrest for general felony while on parole	0	Constant only			1.8049	0.625	2.889
		1	Age at time of first criminal arrest	1		-0.1272	0.348	-3.661
		2	Marital status at time of current offense (0=Married; 1=Single)	1		0.3608	0.135	2.682
		3	Race (0=White; 1=Nonwhite)	1		0.3190	0.125	2.547
6	Arrest for general felony while on parole (excluding marital status and race as predictors)	0	Constant only			-0.4233	0.473	0.895
		1	Age at time of first criminal arrest	1		Removed in Final Step		
		2	Number of years of street time since 14 years of age	1		-0.1298	0.263	-4.936
		3	Number of prior arrests	1		0.8951	0.221	4.046
		4		1	Age at time of first criminal arrest	Removed in Final Step		
		5	Escape	1		-0.9045	0.426	-2.121

the entry of this term, as evidenced by the p-value for the chi-square improvement test (p=.020); however, the large p-value for the standard chi-square goodness-of-fit test (p=.999) is misleading due to the large number of cells with expected values less than five. P-values for the D.H. Hosmer and C.C. Brown goodness-of-fit tests (.388 and .570, respectively) indicate the logistic model is a good match for the data in this regression.

The second logistic regression was constructed to predict the criterion measure 'arrest for general felony while on parole.' The predictor measure 'age at first criminal arrest' was the first to enter the equation, followed by marital status and race. Unlike the first regression, in this case it appears that the logistic model is an excellent fit at every step, as evidenced by the large p-values for C.C. Brown and Hosmer goodness-of-fit tests and the small p-values for both the chi-square improvement and standard chi-square goodness-of-fit tests. Finally, the reader may note the negative coefficient for the predictor measure 'age at time of first criminal arrest (see Table 5.22), indicating an inverse (negative) relationship with the criterion.

The third logistic regression was constructed to predict the same criterion as the second, but the predictors of marital status and race were excluded from consideration. Not surprisingly, 'age at the time of first criminal arrest' was the first term to enter; however, when the second ('number of years of street time since 14 years of age') and third ('number of prior arrests') terms were entered, this combination was found to be more effective than 'age at first criminal arrest' (which in turn was not found to contribute significantly to predictions possible with the other two). 'Age at time of first criminal arrest' was therefore removed and the only other term qualified for entry to the equation was 'escape.' As with the second regression, large p-values for both C.C. Brown and Hosmer goodness-of-fit-tests, and small p-values for both chi-square improvement and standard chi-square goodness-of-fit tests indicate an excellent fit of the logistic model at each step. The coefficients for predictor measures 'number of years of street time since 14 years of age' and 'escape' are both negative (see Table 5.22), indicating inverse relationships with recidivism.

Analyses of Predictive Accuracy for the Logistic Regression Models

Each of the six logistic regression models is cross-validated, and calculations of both Mean Cost Rating (MCR) and Improvement Over Chance (IOC) are reported for construction and cross-validation samples in Table 5.23. As may be noted from review of this table, subsamples I (N=304) and II (N=308) alternately serve as construction and cross-validation samples, depending on whether the first three or the last three of the six regressions are being evaluated.

For the first regression MCR is calculated to be .03 for the construction sample and .02 for the cross-validation sample. The regression improved upon predictions based on

Table 5.23. Summary of predictive accuracy statistics computed for construction and cross-validation samples for all six logistic regressions.[a]

Regression Number	Name of Regression	Construction Sample (N)	Cross-Validation Sample (N)	Statistics for Construction Sample		Statistics for Cross-Validation Sample	
				MCR[b]	IOC[c]	MCR	IOC
1	Arrest for violent felony while on parole	I (304)	II (308)	.03	0.6%	.02	0.5%
2	Arrest for general felony while on parole	I (304)	II (308)	.36	17.1%	.17	8.2%
3	Arrest for general felony while on parole (excluding marital status and race as predictors)	I (304)	II (308)	.35	16.9%	.12	6.0%
4	Arrest for violent felony while on parole	II (308)	I (304)	.03	0.5%	.03	0.6%
5	Arrest for general felony while on parole	II (308)	I (304)	.30	14.4%	.17	8.3%
6	Arrest for general felony while on parole (excluding marital status and race as predictors)	II (308)	I (304)	.41	20.2%	.22	10.4%

[a] The 2x2 matrices upon which this table is based are presented in Appendix E.

[b] Mean Cost Rating

[c] Improvement Over Chance

chance alone less than one percent for both construction and cross-validation samples. For regression number two, MCR is calculated to be .36 and .17 for construction and cross-validation samples, respectively. Predictions of arrest for general felony improves upon predictions based upon chance alone by 17.1 percent and 8.2 percent for construction and cross-validation samples, respectively. Values of MCR for regression number three are .35 and .12 for construction and cross-validation samples, respectively. Predictions are improvements over chance alone by 16.9 percent and 6.0 percent for construction and cross-validation samples, respectively.

For regression number four, MCR is calculated to be .03 for both construction and cross-validation samples. Predictions result in improvements over chance of less than one percent for both construction and cross-validation samples. Values of MCR for regression number five are .30 and .17 for construction and cross-validation samples, respectively. Improvements over chance of 14.4 percent for the construction sample and 8.3 percent for the cross-validation sample are observed for this regression. Finally, predictions of arrest for general felony with regression number six resulted in MCR values of .41 and .22 for construction and cross-validation samples, respectively. Improvements over chance for this regression were the highest obtained in this series of regressions, calculated at 20.2 percent and 10.4 percent for construction and cross-validation samples, respectively.

Chapter Summary

Univariate descriptive statistics are provided in the first section of the chapter. Means and standard deviations are reported for continuous operational measures of predictor variables, and frequency counts with percentages are listed for categorical operational measures of both predictor variables and the criterion. Although descriptive statistics are provided for all measures of each predictor variable and the criterion, there are a number of highlights which stand out. Concerning criminal history, 30 percent of the parolees studied had been charged with felonies as juveniles and 85 percent of the parolees had been arrested previously for felonies (prior to current offense) as adults. These characteristics, combined with the relatively large mean numbers of prior arrests and prior nonviolent felony charges for this group of parolees (approximately 6 and 3.5, respectively), indicate that the majority of parolees in the study began their criminal careers as adults and continued to engage in criminal activity after release from incarceration, in some cases habitually. While only approximately one-fifth of the total sample of parolees had records of previous dispositions greater than one year for person (violent) offenses, approximately one-half the sample had dispositions greater than one year for property (nonviolent) offenses.

In terms of current offense, burglary, larceny and armed robbery were the most frequent convictions which led to the most recent incarceration for parolees in the study. Each of these offense categories account for approximately one-fifth of the sample. In contrast, only three percent of parolees were serving sentences for escape or jail break prior to their most recent parole. This relatively tiny proportion of individuals serving on current escape or jail break sentences renders this operational measure of questionable utility as a predictor of felonious recidivism.

Approximately one-quarter of the parolees in the study sample had no substance abuse indicated in their histories. Fifty-five percent of parolees had histories of either opiate addiction or heavy hallucinogen use. In contrast, only three percent of the sample had histories of either PCP use or sniffing of volatile substances. Again, such a small number of substance abusers in these categories tends to minimize the potential value of these measures for prediction of felonious recidivism.

Age at first criminal arrest ranged from 7 to 39 years, with a mean of 18 years. Age at the time of most recent parole ranged from 18 to 70 years with a mean of 29 years. Finally, in terms of the criterion variable, base rates for violent felony arrest and general (violent or nonviolent) felony arrest are approximately 12 percent and 42 percent, respectively.

None of the 23 operational measures of criminal history were significantly ($p < .05$) related to the criterion measure 'arrest for violent felony on parole' across both subsamples. Only eight of the operational measures of criminal history were significantly related to the criterion measure 'arrest for general felony on parole.' These included: 'number of years of street time since 14 years of age'; 'proportion of years of street time to calendar time since 14 years of age'; numbers of prior nonviolent felony charges in the last 12 months, 24 months, 36 months and 5 years of street time; 'number of prior juvenile commitments'; and 'evidence of juvenile felony.'

No operational measures of either current offense or substance abuse history were significantly related with either of the operational measures of felonious recidivism across both subsamples. While no operational measures of age were significantly related with the criterion measure 'arrest for violent felony' across both subsamples, both operational measures of age ('age at time of parole' and 'age at time of first criminal arrest') were significantly related with the criterion measure 'arrest for general felony' across both subsamples.

For the first of the six logistic regression equations developed, the only predictors which met the entry criteria were 'age at time of parole' (which had an inverse relationship with recidivism) and 'person (violent) disposition greater than one year.' The other equation developed to predict 'arrest for violent felony on parole' (No. 4) included only one predictor: 'number of violent felony charges in last five years of street time.'

Regressions numbered two and five were constructed for prediction of 'arrest for general felony while on parole.' Terms which met the criteria for entry to the first of these equations were, in order of entry, 'number of nonviolent felony charges in last 24 months of street time,' 'number of years of street time since 14 years of age' (inversely related with recidivism), race, substance abuse history and 'number of violent felony charges in last 12 months of street time' (inversely related with recidivism). Predictors which met the criteria for entry to the second of these equations were, in order of entry, 'age at time of first criminal arrest' (inversely related with recidivism), 'marital status at time of current offense,' and race.

The last two of the six regressions (Nos. 3 and 6) were developed to predict 'arrest for general felony while on parole,' but the predictors 'marital status' and 'race' were excluded from consideration for entry to prediction equations. Apart from the exclusion of race, predictors qualifying for entry to the first of these equations (No. 3) were identical (including order of entry) to those selected on the same construction sample when marital status and race were considered for entry. In contrast, predictors which entered and remained to the last step in the second of these regressions (No. 6) were completely different from those selected when marital status and race were considered for entry. These terms included, in order of entry, 'number of years of street time since 14 years of age' (inversely related with recidivism), 'number of prior arrests' and 'escape' (inversely related with recidivism).

Finally, when values of Mean Cost Rating were computed for cross-validation samples, none of the six regression equations resulted in a value which equalled or exceeded .40, either for prediction of violent or general felony arrest on parole.

CHAPTER VI

Discussion

For ease of reference and consistency of presentation, this chapter follows the order of testable hypotheses (H) and variables in the study from previous chapters.

Criminal History

H1(a). Results regarding this hypothesis are contrary to those expected since no operational measures of criminal history were found to be related to 'arrest for violent felony on parole' across both subsamples. Upon examining the nature of the measures found to be effective predictors in either of the two subsamples, however, these relationships could have been expected. Numbers of violent felony charges in the last 36 months of street time, in the last 5 years of street time, and in total, were found to be related to the criterion measure. In addition, the presence of a past person (violent) disposition greater than one year was found to be related to the criterion. These predictors are very violence-specific. Prior nonviolent felony charges and property dispositions greater than one year are not related to the criterion 'arrest for violent felony on parole.' It is uncertain why numbers of violent felony charges in the last 12 months and 24 months of street time were not related to this criterion, but likely one major influence is the relatively low percentage of parolees with more than one prior violent felony or prior person (violent) disposition greater than one year (approximately 22 percent).

Since total prior violent felony charges is related to the criterion, there is evidence to support Farrington's (1982) conclusion that the probability of subsequent conviction for violence increased after each conviction for violence.

Both measures of street time (number of years since 14 years of age, and proportion of street time to calendar time in years since 14 years of age) are related to this criterion for one of the subsamples. The proportional measure was used (to this author's knowledge) for the first time in this study and shows considerable promise for the future as a predictor of parole recidivism.

H1(b). This research hypothesis received some support with 8 of the 23 operational measures of criminal history related to the criterion of general felony arrest on parole across both subsamples. Four of the five measures of prior nonviolent felony charges are related to this criterion across both subsamples, but none of the measures of prior violent felony charges were found to have a significant association across both subsamples. Also the presence of a past property (nonviolent) but not person (violent) disposition greater than one year is related to the criterion for one of the subsamples. These findings reaffirm the criterion-specific nature of parole recidivism predictors, which was noted relative to the violent felony arrest criterion.

Again, both street time measures are related to the criterion. Unlike the significant predictors of 'arrest for violent felony on parole,' number of prior juvenile commitments is related to this criterion across both subsamples, and numbers of prior arrests and major non-bondable misconducts are related to this criterion for one of the two subsamples. Boudouris (1983) and Greenwood (1982) both found past commitments to state juvenile facilities predictive of general adult criminality. The finding that major non-bondable misconducts are related to the criterion is consistent with results reported from earlier studies (Anthony & Oldroyd, 1974; Murphy, 1980; Rans, 1982; State of Michigan, 1978). Evidence of a juvenile felony was also related to the criterion across both subsamples. Anthony and Oldroyd (1979), Monahan (1978) and Wentz and Oldroyd (1979) all found that the mere presence of a juvenile record is an excellent predictor of adult criminality.

Somewhat surprisingly, evidence of any prior felony arrest (felony history) is not related to the criterion 'violent felony arrest on parole,' but is related to the criterion 'general felony arrest on parole' for one of the two subsamples. One reason for this may be that if parolees had prior felonies they would more likely be non-violent than violent. This higher proportion of past nonviolent felonies would violate the criterion-specificity for 'violent felony arrest,' thereby rendering the measure a poor predictor of arrest for violent felony on parole.

One significant association that appears to violate this principle of criterion-specificity is observed in one subsample between the criterion measure 'arrest for general felony' and the criminal history measure 'number of violent felony charges in the last 12 months of street time.' Upon closer examination, however, the negative regression coefficient for this predictor relative to 'arrest for general felony' indicates that 'number of violent felony charges in the last 12 months of street time' is inversely related with this criterion. Perhaps this is evidence of a deterrence phenomenon for parolees with prior convictions for violent crimes, noted by McCleary (1978) and others (Boudouris, 1983; Gottfredson, 1967). It is suggested that such offenders will be less likely, and slower, to recidivate because past violent offenses carried more sure convictions and prison sentences than property crimes and because convictions for past violent crimes likely resulted in longer prison sentences, thereby increasing the motivation of parolees to avoid future arrest. Petersilia (1985b) found that property (nonviolent) offenders recidivated both more quickly and more often than person (violent) offenders.

Current Offense

H2(a). Neither the Michigan Current Offense code nor the predictor measure 'serving on current escape or jail break sentence' was related to the criterion 'arrest for violent felony on parole,' in either subsample, as hypothesized. Collapsing offenses into similar categories and differentiating between high-recidivism and low-recidivism current offenses, as in the current offense code for the Iowa model (Fischer, 1985), would likely increase the strength of relationship between measures of current offense and this criterion. The potential useful- ness of the current escape measure is severely limited because only three percent of the parolees studied had recently been serving on a current escape or jail break sentence.

H2(b). Not surprisingly, given the tiny percentage of parolees in the sample who had recently served prison time for a current escape or jail sentence, this measure was not related to the criterion measure 'arrest for general felony on parole' for either subsample. Neither was the Michigan Current Offense code.

Past studies have reported excellent results using only dichotomies for current offense, such as person-property or violent-nonviolent distinctions (Dean, 1968; Forst, et al., 1983). Possibly such a dichotomy would prove more useful than the extended ordinal scale for current offense incorporated in the present study.

Substance Abuse History

H3(a). No operational measures of substance abuse history are significantly related with the criterion measure 'arrest for violent felony' in either subsample. One major problem with the substance abuse scales used in the study is that they are all cumulative, ordinal measures rather than clear categorical divisions of substance abuse types. An attempt was made to reduce this problem in the study by artificially dichotomizing the substance abuse categories (see Chapter IV and Appendix D for details concerning recoding); however, these dichotomous measures were still not discrete substance abuse types. Most of the studies with favorable results concerning the relationship between substance abuse and recidivism incorporate mutually exclusive substance abuse categories rather than ordinal scales (Ladouceur & Temple, 1985; Monahan, 1981; Pritchard, 1979).

H3(b). For reasons discussed relative to the previous hypothesis, it was not surprising that substance abuse measures were not related to the criterion measure 'arrest for general felony on parole across both subsamples. Ladouceur and Temple (1985) reported from their review of literature that alcohol abuse was more frequently related with violent and sex-related crimes than other forms of substance abuse, but they failed to support this hypothesis with their own findings. Sanchez (1986) also failed to find significant relationships between measures of past substance abuse and later recidivism.

Age

H4(a). The predictors 'age at time of parole' and 'age at time of first criminal arrest' are not related to 'arrest for violent felony' across both subsamples but are related to 'arrest for general felony on parole,' indicating that this measure is a good predictor of general felonious recidivism but not specifically violent felonious recidivism. Petersilia and Honig (1980) and Bonham and his colleagues (1984) all found only modest associations between recidivism and age at release on parole. Part of the explanation for the relatively weak associations found between operational measures of age and recidivism in these studies may be that the operational measure(s) of recidivism used incorporated higher proportions of violent felonies than other studies incorporating age-related predictors.

H4(b). As hypothesized, the variable age (particularly the operational measure 'age at time of first criminal arrest') is inversely related to the criterion 'arrest for general felony on parole' across both subsamples. This finding is consistent with past research by Anthony and Oldroyd (1979), Fischer (1983b), Greenwood (1982), Pritchard (1979), Wainer and Morgan (1982) and Wentz and Oldroyd (1979). Gendreau and his colleagues (1980) found this measure to be the best single predictor of recidivism. Both operational measures of age are negatively related to 'arrest for general felony on parole' and this finding is completely consistent with results of past research (Dean, 1968; Hirschi and Gottfredson, 1983). This inverse relationship between age and felonious recidivism on parole involves both a "youthfulness" effect, whereby parolees under 30 years of age are substantially more likely to recidivate than older parolees (Sanchez, 1983) and a "burn-out" effect, whereby parolees over 45 years of age are much lower risks than younger men (Forst, et al., 1983; Gottfredson, 1967; Hoffman and Beck, 1984; Monahan, 1981).

Before proceeding to discuss results relative to hypothesis five, it would seem reasonable to briefly consider the findings relative to the predictors of 'marital status' and 'race.' As Monahan (1981), among others, has stressed after extensive reviews of the literature pertaining to prediction of violent and general recidivism, race has consistently been found to be an outstanding predictor. This was again demonstrated in this study. Reports for series of studies in Michigan consistently found marital status to be among the better predictors of recidivism on parole (Murphy, 1980; 1985; State of Michigan, 1978). This association, too, was demonstrated in the present study. As mentioned in Chapter II, since a good deal of controversy surrounds these variables even though they are good predictors (Zwanenburg, 1977), logistic regression models were constructed with, and without, these predictors.

Development and Assessment of Predictive Accuracy of the Logistic Regression Models

Considerable justification was provided in the Methods Chapter (IV) for selection of stepwise logistic regression rather than multiple linear regression or multiple linear discriminant analysis for development of predictive models in this study. A major limitation of the procedure, however, is that no values are provided to indicate the extent to which variance in the criterion is explained by variance in the combination of predictors. Further, although observed significance levels are given to indicate the significance of relationships between predictors and criterion measures, one has difficulty conceptualizing these as measures of strength of association in the same way one would use correlation coefficients. With these concerns aside, however, there are no results from the study which would contraindicate the application of this procedure for use in future parole prediction research. Although assessments of predictive accuracy for the logistic models indicate relatively poor performance, this is not necessarily due to an inherent weakness of logistic regression.

In terms of selection of operational measures of predictor variables for inclusion in prediction equations, findings were consistent with those reported and discussed previously relative to bivariate associations between predictors and the criterion. As with least-squares estimation procedures, logistic regression (which incorporates maximum likelihood estimation) selects terms at each step which have the most significant associations with the criterion, partialling out the contributions of predictors entered at earlier steps. This explains the consistency between variables found to have significant bivariate relationships with the criterion and those which entered the multivariate equations. Since all operational measures of these predictor variables in the regression models were discussed relative to past recidivism prediction research in the previous section of this chapter, discussion in the remainder of this section will be confined to the fifth and sixth hypotheses.

H5. It was hypothesized that predictions of general felony arrest on parole from applications of logistic regression prediction models would result in values of Mean Cost Rating equal to, or greater than, .40. Findings were disappointing. None of the four models developed to predict arrest for general felony reached this level of predictive efficiency when applied to cross-validation samples. This was not likely due to the base rate, since this was approximately 42 percent for both subsamples. Neither, it would seem, was this due to instability of predictors, since most predictors which entered the equations were very objective measures ('age at time of parole', etc.) found to be significantly related to the criterion across both subsamples. Further, most of these predictors have very consistently been demonstrated to be very good predictors of felonious recidivism in other studies. This lack of predictive efficiency is more likely due to a lack of comprehensive coverage of a wide enough range of types of predictors. As Dean (1968) criticized, most actuarial variables are too "static."

Even when applied to construction samples, only one of the six models provided predictions resulting in a Mean Cost Rating which exceeded a value of .40. This model also resulted in achievement of the highest level of predictive accuracy and efficiency of the six regressions when applied to the cross-validation sample (Mean Cost Rating of .22 and Improvement Over Chance of 10.4 percent). The two key terms in this equation are 'number of years of street time since 14 years of age' (inversely related with general felony arrest) and 'number of prior arrests.' This combination makes considerable intuitive sense, since together these measures constitute an assessment of the "density" of prior criminal activity. The third measure which entered this equation was 'escape' (serving sentence for escape or jail break). The negative coefficient for this predictor may indicate a "deterrence" phenomenon similar to that discussed relative to the use of prior violent felony charges to predict general felony arrest on parole. The premise underlying such a phenomenon would be that a recent additional period of incarceration would motivate offenders released on parole to avoid criminal activity, thereby preventing future arrests.

H6. It was hypothesized that logistic regressions developed to predict arrest for violent felony on parole would result in relatively inaccurate predictions (specifically, that values of Mean Cost Rating would not equal or exceed .40). This hypothesis was well supported, since neither regression developed to predict this criterion measure resulted in even one percent improvement upon chance alone. This was very likely due to the low base rate (12 percent) for this criterion. In addition, since no operational measures of predictor variables were related with this criterion across both subsamples, it appears that no stable relationships exist between this criterion and the predictor measures employed in the study. This lack of stability alone could explain the absence of relationship observed with the criterion. Suggestions for improvement of predictions are provided in the next chapter, along with conclusions pertaining to each of the general hypotheses listed in Chapter I.

CHAPTER VII

Conclusions and Recommendations for Future Research

The American Psychological Association (APA, 1983) suggests that the abstract constitutes the summary in a doctoral dissertation. Following this advice, the present chapter includes only conclusions and recommendations for future research.

Conclusions

Hypothesis 1

Eight operational measures of criminal history are related to recidivism on parole when the criterion is 'arrest for general felony,' but none are related when the criterion is 'arrest for violent felony.' Hence, the hypothesized relationship between these measures receives partial support from results.

Hypothesis 2

Current offense for parolees is not related to recidivism on parole for either the criterion 'arrest for violent felony' or 'arrest for general felony.' Hence, the hypothesized relationship between these measures is supported by results.

Hypothesis 3

Substance abuse history of parolees is not related to recidivism on parole. This conclusion is contrary to the hypothesized relationship between these variables.

<u>Hypothesis 4</u>

Age of parolees is negatively related with recidivism on parole for the operational criterion measure 'arrest for general felony' but is not related with the criterion measure 'arrest for violent felony.' This conclusion is consistent with the hypothesized relationship between these variables.

<u>Hypothesis 5</u>

Predictions of arrest for general felony on parole using logistic regressions developed in the study for this purpose do not equal or exceed the accuracy of those reported for most other current recidivism prediction models or instruments. Hence this hypothesis received no support from results.

<u>Hypothesis 6</u>

Predictions of arrest for violent felony on parole using logistic regressions developed in the study for this purpose do not equal or exceed the accuracy of those reported for most other current recidivism prediction models or instruments. Hence, this hypothesis is well supported by results of the study.

<u>Recommendations for Future Research</u>

Further use of the criterion measures 'arrest for violent felony while on parole' and 'arrest for general felony of parole' is recommended; however, the criterion measure arrest for violent felony should be restricted to samples with base rates for violent felonies in excess of 30 percent. For low base rate events, it is extremely difficult to improve substantially upon predictions based upon chance alone.

Detailed adherence to, and reporting of, descriptions of operational measures of criterion and predictor variables cannot be overstressed. Often comparisons of results between studies is severely limited because the computations or coding formats of such measures are not identical, or at least not directly comparable. Future use of the operational measures of predictor variables found to be significantly related with criterion measures across both subsamples is highly recommended. These measures are described in considerable detail (including coding formats and procedures) in earlier chapters.

Use of stepwise logistic regression in future research is highly recommended when operational measures of recidivism are dichotomous, particularly if assumptions underlying discriminant function and multiple linear regression analyses appear to be violated. This statistical procedure has been used very effectively for many years in medical research (with 'survival' or 'mortality' data); however, the widespread adoption of this method for use in the social sciences has yet to occur. Experimentation with cost matrices for prediction outcomes (available in BMDP program P:LR) could also produce some very useful information and prove useful to criminal justice and social service administrators to assist in decision-making. This differential weighting of prediction outcomes has been used very effectively by Loeber and Dishion (1983) with criminal justice data. Continued use of Mean Cost Rating (MCR) and Improvement Over Chance (IOC) statistics to describe predictive accuracy and efficiency is also encouraged.

Further research should include operational measures of criminal history from several levels or steps in the criminal justice process, including charges, arrests, convictions, sentences (dispositions) and commitments (incarcerations). Current offenses should be clustered into a small number of homogeneous categories (even into violent/nonviolent or property/person offense dichotomies). High recidivism offenses should be grouped separately from low-recidivism offenses.

Substance abuse history should be measured using clearly-defined, mutually exclusive categories (alcoholism, opiate addiction, etc.) rather than ordinal scales which consist of only the "highest level" or "most severe form" of substance abuse for each parolee. Finally, operational measures of age, including 'age at time of first criminal arrest' and 'age at parole' should definitely be used in future parole recidivism prediction research, since these are two of the most stable, robust predictors available.

Entire realms of potential predictors of recidivism remain unexplored. Dean (1968) has developed a number of unorthodox measures to tap such domains and found that they seem to provide "explanation" for, or at least association with, aspects of recidivism which remain untapped with most standard actuarial variables. Such possibilities are thoroughly deserving of future research.

In spite of the fact that the most consistently effective predictors of recidivism were used and considerable effort was expended to improve upon the weaknesses of past research, predictions are not sufficiently accurate to be applied in parole decision-making. One inherent problem with such research (for which no solution is available) is that samples of parolees are already biased, since all inmates eligible for parole are not released. Even the parole recidivism prediction model reputed to be the best available (Iowa Offender Risk Assessment) has not resulted in even reasonably accurate predictions (Mean Cost Ratings of .20 or better) when applied to cross-validation samples in Michigan and Washington. These past failures cast considerable doubt upon the wisdom of embarking upon further recidivism prediction studies of this nature.

APPENDICES

APPENDIX A

RECIDIVISM RISK ASSESSMENT: CURRENT MODELS AND INSTRUMENTS

Item A .... ☐
No prior convictions (adult or juvenile) = 3
One prior conviction .... = 2
Two or three convictions .... = 1
Four or more prior convictions ...... = 0

Item B .... ☐
No prior commitments (adult or juvenile) = 2
One or two prior commitments .... = 1
Three or more prior commitments ..... = 0

Item C .... ☐
Age at behavior leading to first commitment (adult or juvenile):
26 or older . = 2
18–25 ..... = 1
17 or younger = 0

Item D .... ☐
Commitment offense did not involve auto theft or check(s)
(forgery/larceny) .... = 1
Commitment offense involved auto theft, or check(s), or both = 0

Item E .... ☐
Never had parole revoked or been committed for a new offense while on
parole, and not a probation violator this time .... = 1
Has had parole revoked or been committed for a new offense while on
parole, or is a probation violator this time, or both .... = 0

Item F .... ☐
No history of heroin or opiate dependence = 1
Otherwise .... = 0

Item G .... ☐
Verified employment (or full-time school attendance) for a total of at least
six months during the last two years in the community = 1
Otherwise .... = 0

TOTAL SCORE .... ☐

Figure A-1. Salient Factor Score (SFS 76).

Score and total the following points according to the indicated characteristics:

Prior convictions or adjudications (adult or juvenile)

None	+3
One	+2
Two or Three	+1
Four or More	0

Prior commitments of more than 30 days (adult or juvenile)

None	+2
One or two	+1
Three or more	0

Age at instant offense*

26 or older	+2
20-25	+1
19 or younger	0

Recent commitment free period during last 3 years

No prior commitment more than 30 days (adult or juvenile), or released to the community at least 3 years before commission of the instant offense	+1
"Otherwise"	0

Probation or parole or confinement escape status this time

No	+1
Yes	0

Heroin or opiate dependence

No history	+1
History	0

*But if the record shows five or more commitments of more than 30 days, this item is scored "0" regardless of the age at the time of the instant offense.

Figure A-2. Federal salient factor score (1981 version).

DANGEROUS AND ADJUSTMENT SCALES FOR INITIAL INSTITUTION SECURITY CLASSIFICATION

DANGEROUS SCALE

1. CURRENT OFFENSE SERIOUSNESS
   Enter 10 if score 5 or higher on the Seriousness Scale, otherwise enter 0 ______
2. EMPLOYMENT
   Enter 10 if unemployed prior to the commission of the offense. If full time, or part time employed, enter 0 ______
3. AGE SCORE
   Enter 7 if 22 or under, otherwise enter 0 ______
4. VIOLENT OFFENSE
   Enter 5 if ever convicted of violent offense against a person, otherwise enter 0 ______
5. EXPECTED LENGTH OF STAY
   Enter 3 if expected stay is greater than 2 years, otherwise enter 0 ______

TOTAL SCORE (Add 1 through 5) ______

ADJUSTMENT SCALE

1. AGE SCORE
   (Subtract 14 from current age) ______
2. NUMBER OF PRIOR CONVICTIONS
   (Does NOT include current)
   Number of convictions x 20 (weight) ÷ age score ______
3. NUMBER OF CONVICTIONS FOR BURGLARY/THEFT
   Number of convictions x 30 (weight) ÷ age score ______
4. NUMBER OF CONVICTIONS FOR VIOLENCE AGAINST PERSON
   Number of convictions x 10 (weight) ÷ age score ______
5. ESCAPE SCORE
   Enter 5 if ever convicted of escape ______
6. CURRENT OFFENSE SERIOUSNESS
   Enter 10 if score is 7 or lower on the Seriousness Scale, otherwise enter 0 ______
7. PRIOR SUPERVISION HISTORY
   If there is a record of a technical or new offense violation while on any supervision, enter 5, otherwise enter 0 ______

TOTAL SCORE* ______

*Danger and Adjustment Scores are Matrixed and Security Designation Assigned

Figure A-3. Illinois dangerousness and adjustment scales.

<u>**Score and total the following points according to the indicated characteristics:**</u>

Heavy use of alcohol	**+ 5**
Heroin use	**+10**
Age at time of instant arrest	
Less than 23	**+21**
23-27	**+14**
28-32	**+ 7**
33-37	**0**
38-42	**- 7**
43+	**-14**
Length of criminal career (since first arrest)	
0-5 years	**0**
6-10 years	**+ 1**
11-15 years	**+ 2**
16-20 years	**+ 3**
21+ years	**+ 4**
Arrests during last 5 years (score each arrest as indicated)	
Crimes of violence	**+ 4**
Crimes against property	**+ 3**
Sale of drugs	**+ 4**
Other offenses	**+ 2**
Longest time served, single term (prior sentence)	
1-5 months	**+ 4**
6-12 months	**+ 9**
13-24 months	**+18**
25-36 months	**+27**
37-48 months	**+36**
49+ months	**+45**
Number of probation sentences (score each as indicated)	**+1.5**
Instant offense was crime of violence	**+ 7**
Instant offense was crime labeled "other"	**-18**

Violent crimes include robbery, homicide, assault, sexual assault, kidnapping, and other crimes against persons. "Other" crimes include all crimes other than arson, burglary, larceny, auto theft, fraud, forgery, drug sale or possession, and violent crimes.

<u>Figure A-4</u>. Inslaw scale.

MICHIGAN DEPARTMENT OF CORRECTIONS
ASSAULTIVE RISK SCREENING SHEET CSO-353 12/77

RESIDENT'S NAME		NUMBER
SCREENED BY	LOCATION	DATE

INSTRUCTIONS: Starting at left, check "yes" or "no" at each item. This directs you to next item. When a risk category is reached at right, circle that category. If information is missing or conflicting, circle insufficient information box and refer to classification director. See definitions on reverse side.

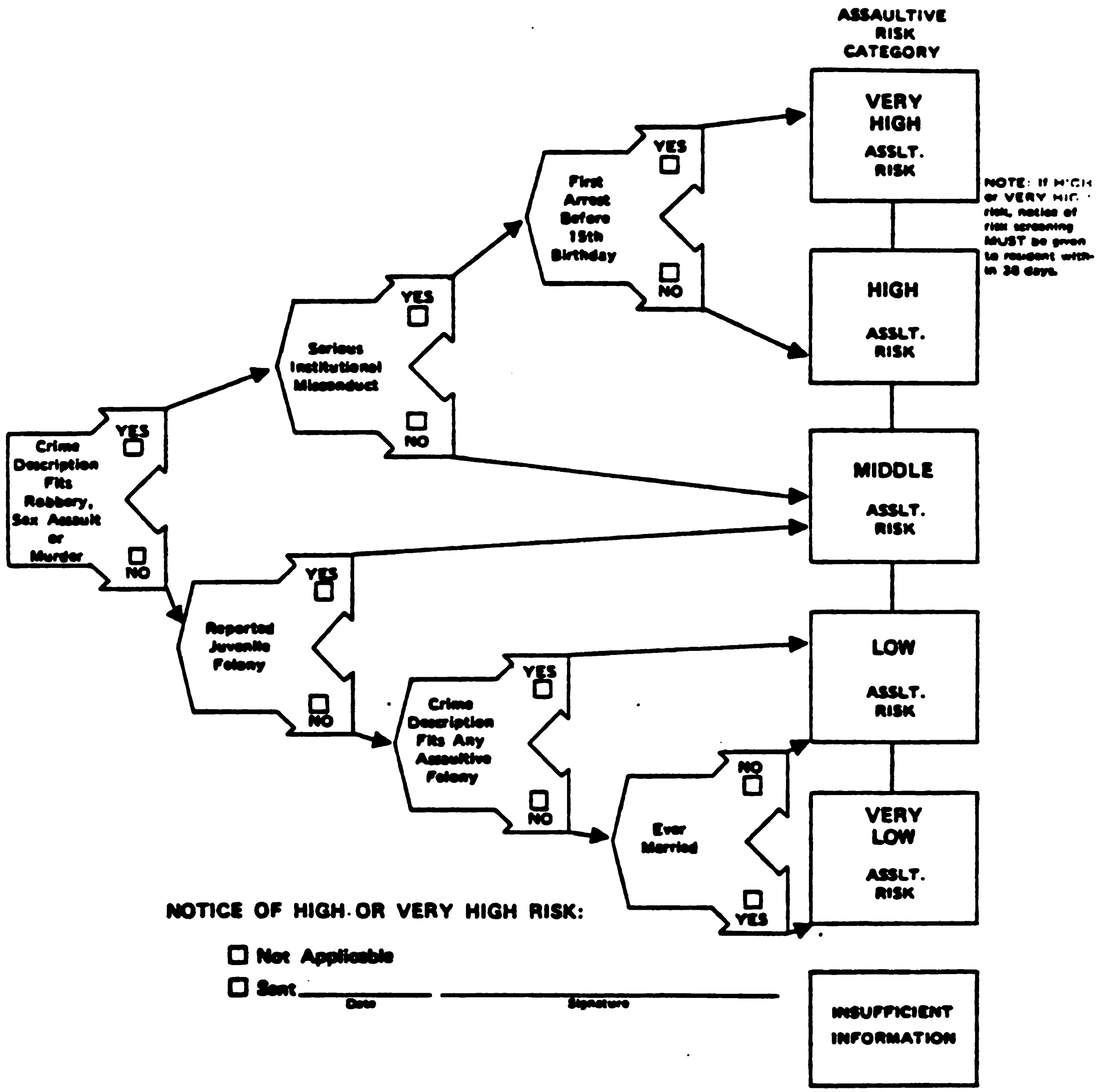


Figure A-5. Michigan assaultive risk screening checklist.

DEFINITIONS OF ASSAULTIVE RISK CLASSIFICATION FACTORS

1. **Serving on robbery, sexual assault, or homicide.** This factor will be coded "yes" if the individual is now serving on and/or has not been discharged from sentence for a felony, the description of which indicates that, by any participant in the crime, there was either: a) the taking or attempt to take property or money by force or threat of force during personal confrontation, b) sexual assault or attempted sexual assault by force or threat of force, or c) death of a victim.

This determination is based on the best judgment of the person doing the coding after review of the investigator's description of the offense, and all other relevant information concerning the offense available. Because the offense of conviction is a result of plea bargaining and other factors not related to behavior during the incident, the coding in the study and, therefore, in its application is based on actual behavior so far as this can be determined from documentation normally available.

2. **Serious misconduct or security segregation.** This variable will be coded "yes" if, during any sentence for which he is still serving, the resident has been a) found guilty of major misconduct which is nonbondable under current department-wide policy by the disciplinary hearing committee, that is, found guilty of homicide, assault, intimidating or threatening behavior, sexual assault, fighting[1] inciting to riot or strike, rioting or striking, or possession of dangerous contraband, or escape, and attempt to escape; OR b) was placed in administrative segregation by the security classification committee. Involuntary segregation for the resident's own protection is not to be counted in this category; neither is segregation within R&GC only.

3. **First arrest before 15 years.** This variable is to be coded "yes" if the presentence report or policy arrest record indicates that the individual was arrested for or had a petition filed for any criminal behavior prior to his 15th birthday.

4. **Reported juvenile felony.** This variable is to be coded "yes" if the record indicates that the individual, before his 17th birthday, has a reported arrest or petition filed for behavior which would constitute a felony for an adult.[2]

5. **Serving on assaultive felony.** The individual shall be coded "yes" on this variable if the description of his behavior during the course of any felony on which he is now serving indicated that it involved harm or threat of harm to any person. This is defined as behavior constituted by any of the felonies listed below.

6. **Ever married.** This variable is to be coded "yes" if the individual, at the time of the commission of the instant offense, was or had ever been legally married. A commonlaw relationship of at least seven years duration shall be counted as equivalent to legal marriage if it can be documented to the satisfaction of the coder.

[1] If the hearing report clearly indicates that the individual was only reacting to attack and had no part in provoking the incident it should not be counted here.

[2] Incarceration or probation for criminal behavior will be taken as evidence of petition or arrest. Status offenses are not to be counted.

OFFENSES TO BE REGARDED AS ASSAULTIVE FOR PURPOSES OF RISK CLASSIFICATION

M.C.L.	750.316	Murder, First
	750.317	Murder, Second Degree
	750.91	Attempt to Murder
	750.321	Manslaughter
	750.324	Negligent Homicide
	750.83	Aslt W/Intent to Commit Murder
	750.349	Kidnapping
	750.82	Felonious Assault
	750.84	Aslt W/Int Gr Bod Harm Less Murder
	750.89	Aslt W/Int to Rob & Steal Armed
	750.87	Aslt W/Int to Commit Felony
	750.479A	Driver Assault Police
	750.88	Aslt W/Int to Rob & Steal Unarmed
	750.136	Cruelty to Children
	750.529	Robbery Armed
	750.530	Robbery Unarmed
	750.205	Place Explosive By Prop W/Int Dist
	750.209	Place Off. Subst. W/Int to Injure
	750.210	Possession of Bomb
	750.211A	Explosive Devices, Use or Possess
M.C.L.	752.861	Careless Use of Firearms to Kill
	750.479	Resisting, Obstructing Officer
	752.542	Incite, Take Part in Riot
	750.197C	Jail Break - Armed
	752.191	Felonious Driving
	750.85	Aslt W/Int to Rape
	750.158	Sodomy
	750.333	Incest
	750.336	Indecent Liberties
	750.338/338A/338B	Gross Indecency
	750.339/340	Debauchery
	750.341/342	Carnal Knowledge
	750.520	Rape (Incl. Statutory)
	750.520b	Criminal Sexual Conduct, First Degree
	750.520c	Criminal Sexual Conduct, Second Degree
	750.520d	Criminal Sexual Conduct, Third Degree
	750.520g	Aslt W/Int to Com Crim Sex Conduct
	767.61A	Offenses by Sexually Delinquent
	750.71-80	Arson*

*Except where the arson can clearly be established to have taken place only for purposes of profit and without risk to life or safety.

Figure A-5 (cont'd.)

MICHIGAN RISK SCREENING

Original Michigan Definition		Current Study Definition
Property Risk	Assaultive Risk	Assaultive/Property Risk
High Risk	Very High Risk	Very High Risk
	High Risk	Very High Risk
	Middle Risk	High Risk
	Low Risk	High Risk
	Very Low Risk	High Risk
Middle Risk	Very High Risk	High Risk
	High Risk	High Risk
	Middle Risk	Middle Risk
	Low Risk	Middle Risk
	Very Low Risk	Low Risk
Low Risk	Very High Risk	Middle Risk
	High Risk	Middle Risk
	Middle Risk	Low Risk
	Low Risk	Low Risk
	Very Low Risk	Low Risk

Figure A-5. (cont'd.)

MICHIGAN DEPARTMENT OF CORRECTIONS
PROPERTY RISK SCREENING SHEET

RESIDENT'S NAME		NUMBER
SCREENED BY	LOCATION	DATE

INSTRUCTIONS: Starting at left, check ✓ "yes" or "no" at each item. This directs you to next item. When a risk category is reached at right, circle that category. If information is missing or conflicting, circle insufficient information box and refer to classification director. See definitions on reverse side.

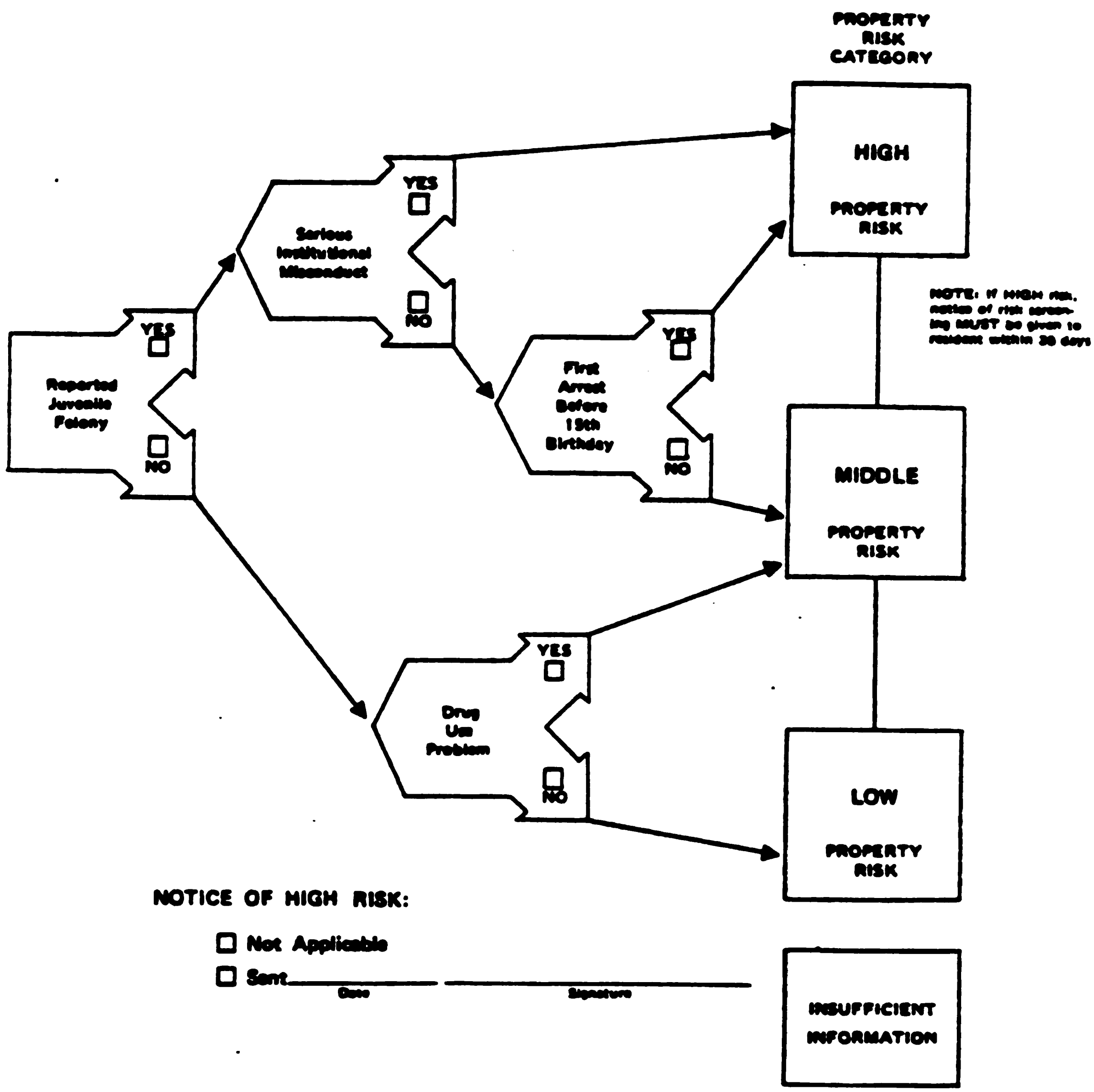


Figure A-6. Michigan property risk screening checklist.

DEFINITIONS OF PROPERTY RISK CLASSIFICATION FACTORS

1. **Reported juvenile felony.** This variable is to be coded "yes" if the record indicates that the individual, before his 17th birthday, has a reported arrest or petition filed for behavior which would constitute a felony for an adult.[2]

2. **Serious misconduct or security segregation.** This variable will be coded "yes" if, during any sentence for which he is still serving, the resident has been a) found guilty of major misconduct which is nonbondable under current department-wide policy by the disciplinary hearing committee; that is, found guilty of homicide, assault, intimidating or threatening behavior, sexual assault, fighting,[1] inciting to riot or strike, rioting or striking, or possession of dangerous contraband, or escape, and attempt to escape; OR b) was placed in administrative segregation by the security classification committee. Involuntary segregation for the resident's own protection is not to be counted in this category; neither is segregation within R&CG only.

3. **First arrest before 15 years.** This variable is to be coded "yes" if the presentence report or police arrest record indicates that the individual was arrested for or had a petition filed for any criminal behavior prior to his 15th birthday.

4. **Drug use problem.** This variable shall be coded "yes" if and only if the individual, at or about the time of any offense on which he is now serving, was: a) addicted to any nonprescribed controlled substance other than marijuana or alcohol, or b) in chronic or sustained use of any nonprescribed controlled substance other than marijuana or alcohol. Occasional use is not to count, nor is addiction or sustained use which apparently terminated at least six months before the instant offense. It is recognized that this variable will be difficult to code, and information will often be lacking. The coder's best judgment, based on material present in the written record, must be the basis.

[1] If the hearing report clearly indicates that the individual was only reacting to attack and had no part in provoking the incident it should not be counted here.

[2] Incarceration or probation for criminal behavior will be taken as evidence of petition or arrest. Status offenses are not to be counted.

Figure A-6. (cont'd.)

Client's Name______________________

Offense______________________

State of
Oregon

CRIMINAL HISTORY/RISK ASSESSMENT UNDER RULE 255-35-015

A.	No prior felony or misdemeanor convictions as an adult or juvenile.*	3
	One prior conviction:	2
	Two or three prior convictions:	1
	Four or more prior convictions:	0______
B.	No prior incarcerations (i.e., executed sentences of 90 days or more) as an adult or juvenile:	2
	One or two prior incarcerations:	1
	Three or more prior incarcerations:	0______
C.	Age at first commitment of 90 days or more: **	
	26 or older:	2
	21 to under 26 :	1
	Under 21 :	0______
D.	Never escaped, failed parole or probation: ***	2
	One incident of the above:	1
	Any two or more incidents of the above :	0______
E.	Has no admitted or documented heroin or opiate derivative abuse problem, or has no admitted or documented alcohol problem :	1
	One or more of the above :	0______
F.	Verified period of 3 years conviction free in the community prior to present offense:	1
	Otherwise :	0______
TOTAL HISTORY/RISK ASSESSMENT SCORE:		______

*Do not count convictions over 20 years old, convictions that have been pardoned, or juvenile or adult "status offenses" (runaway, truancy, incorrigibility, drunk in public).

**If no prior commitment, use age at present conviction.

*** Count probation failure only if it resulted from an executed sentence of 90 days or more; count any parole failure, including parole reinstatement under rule 254-175-080.

CRIMINAL HISTORY/RISK ASSESSMENT SCORE:	11-9 EXCELLENT	8 -6 GOOD	5 -3 FAIR	2 -0 POOR
OFFENSE SEVERITY RATING: (All ranges in Categories 1-6 shown in months)				
Category 1	6	6	6-10	12-18
Category 2	6	6-10	10-14	16-24
Category 3	6-10	10-14	14-20	22-38
Category 4	10-16	16-22	22-30	32-44
Category 5	18-24	24-36	40-52	56-72
Category 6	30-40	44-56	60-80	90-130
Category 7				
Subcategory 2	8-10 Yrs	10-13 Yrs	13-16 Yrs	16-20 Yrs
Subcategory 1	10-14 Yrs	14-19 Yrs	19-24 Yrs	24-life Yrs

* The Minimum Term for murders committed after December 7, 1978, shall be twenty-five (25) years as required by ORS 163.115.

____
Counselor

Figure A-7. Oregon criminal history/risk assessment.

RAND SCALE

Score one (1) point for each of the following characteristics:

- Prior conviction (juvenile or adult) for the instant offense type
- Incarcerated more than 50% of preceding two years
- Conviction before age 16
- Served time in state juvenile facility
- Heroin or barbiturate use in preceding two years
- Heroin or barbiturate use as a juvenile
- Employed less than 50% of the preceding two years

Figure A-8. Rand 7-factor score.

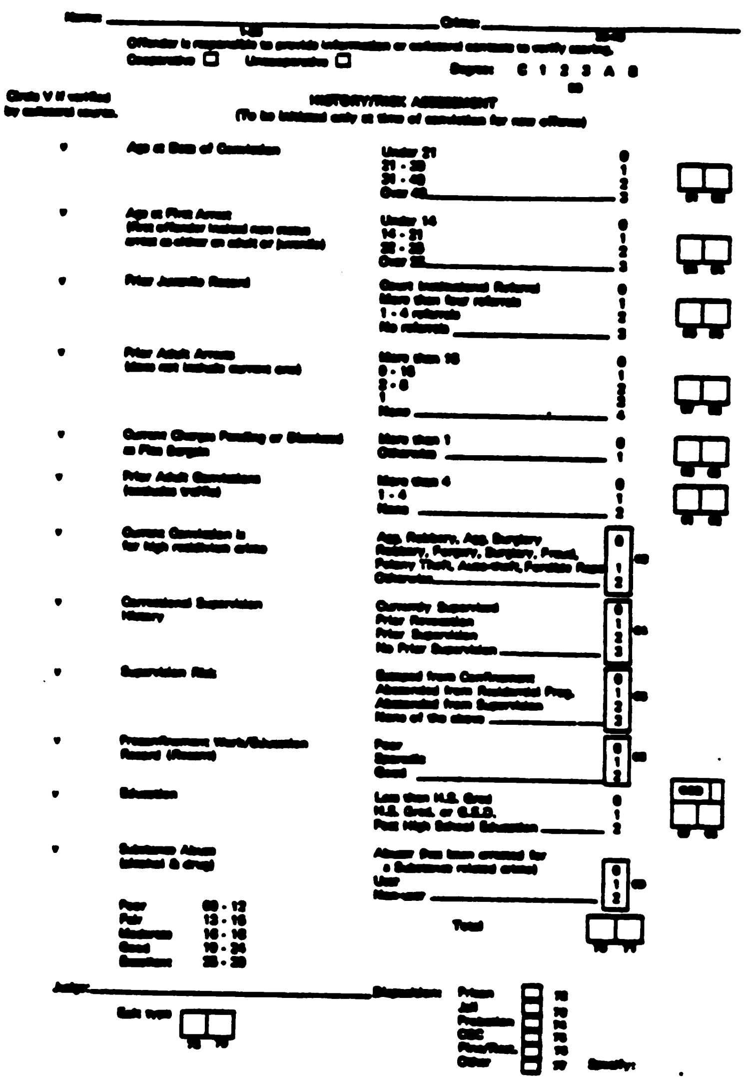


Figure A-9. Utah history/risk assessment

Select the appropriate answer and enter the associated weight in the score column.

			SCORE
Number of Address Changes in Last 12 Months: (Prior to incarceration for parolees)	0 2 3	None One Two or more	____
Percentage of Time Employed in Last 12 Months: (Prior to incarceration for parolees)	0 1 2 0	60% or more 40% - 59% Under 40% Not applicable	____
Alcohol Usage Problems: (Prior to incarceration for parolees)	0 2 4	No interference with functioning Occasional abuse; some disruption of functioning Frequent abuse; serious disruption; needs treatment	____
Other Drug Usage Problems: (Prior to incarceration for parolees)	0 1 2	No interference with functioning Occasional abuse; some disruption of functioning Frequent abuse; serious disruption; needs treatment	____
Attitude:	0 3 5	Motivated to change; receptive to assistance Dependent or unwilling to accept responsibility Rationalizes behavior; negative; not motivated to change	____
Age at First Conviction: (or Juvenile Adjudication)	0 2 4	24 or older 20 - 23 19 or younger	____
Number of Prior Periods of Probation/Parole Supervision: (Adult or Juvenile)	0 4	None One or more	____
Number of Prior Probation/Parole Revocations: (Adult or Juvenile)	0 4	None One or more	____
Number or Prior Felony Convictions: (or Juvenile Adjudications)	0 2 4	None One Two or more	____
Convictions or Juvenile Adjudications for: (Select applicable and add for score. Do not exceed a total of 5. Include current offense.)	2 3	Burglary, theft, auto theft, or robbery Worthless checks or forgery	____
Conviction or Juvenile Adjudication for Assaultive Offense within Last Five Years: (An offense which involves the use of a weapon, physical force or the threat of force)	15 0	Yes No	____
		TOTAL	____

Figure A-10. Wisconsin risk assessment.

1984 Version

OFFENDER RISK ASSESSMENT
THE IOWA MODEL

G	V	CURRENT OFFENSE SCORE (A)
2	3	Robbery/Attempted Robbery
2	3	Larceny from a Person
2	3	Aggravated Burglary
2	3	Arson/Attempted Arson
1	3	Murder/Attempted Murder
1	3	Manslaughter
1	3	Kidnapping
1	3	Rape/Attempted Rape
1	3	Sodomy
2	1	Burglary/Attempted Burglary
2	1	Selling Narcotics
2	1	Motor Vehicle Theft
2	1	Forgery/Bad Checks/Fraud
1	1	Aggravated Assault/Terrorism
1	1	Extortion
1	1	Going Armed with Intent
1	1	Conspiracy to Commit a Violent Felony
1	1	Larceny/Stolen Property
1	0	Vandalism
1	0	Weapons Offense
1	0	Conspiracy to Commit a Non-Violent Felony (above)
0	0	None of Above

G	V	PRIOR VIOLENCE SCORE (B)
4	5	91+
2	3	11-90
0	0	0-10

G	V	STREET TIME SCORE (C)
3	3	0-6 Years
2	2	6-11 Years
1	1	11-14 Years
0	0	14+ Years

G	V	CRIMINAL HISTORY SCORE (D)
6	6	140+
3	5	41-139
1	1	16-40
0	0	0-15

G	V	CURRENT ESCAPE SCORE (E)
3	4	Convicted
1	2	Arrested/Charged Only
0	0	Not as Above

G	V	SUBSTANCE ABUSE SCORE (F)
5	7	History of PCP Use
5	7	History of Non-Opiate Injections
5	7	History of Sniffing Volatile Substance
4	4	History of Opiate Addiction
3	4	History of Heavy Hallucinogen Use
2	1	History of Drug Problem
1	1	History of Opiate or Hallucinogen Use
1	1	History of Alcohol Problem
0	0	No History as Above

SERIOUS OFFENDER CLASSIFICATION

Yes	Current Conviction for Violent Felony
Yes	Current Conviction for Escape/Jailbreak/Flight
Yes	Prior Conviction for Felony Against Persons in Last Five Years Street Time
Yes	Prior Violence Score 35+
Yes	Substance Abuse Score 7
No	No Factor as Above

G	V	
___	___	X-SCORE = A + B + C
___	___	Y-SCORE = D + E + F

GENERAL RISK ASSESSMENT

	X-SCORE				
Y-SCORE	0-1	2-3	4	5	6+
0	E	E	E	E	P
1	E	E	G	G	P
2	E	G	G	P	P
3-4	E	G	P	P	P
5	E	P	P	P	VP
6	P	P	P	P	VP
7	P	P	P	VP	VP
8+	P	P	VP	VP	VP

VIOLENCE RISK ASSESSMENT
(*Higher Rating for Serious Offender*)

	X-SCORE						
Y-SCORE	0	1-2	3	4-5	6-7	8	9+
0	E	E	E	E	G	G	F/P
1	E	E	E	G	G/F	F/P	F/P
2-3	E	G	G	G	F/P	F/P	F/P
4-6	E	G/F	F	F/P	F/P	F/P	F/VP
7-8	F	F	F/P	F/P	F/P	F/VP	F/VP
9+	F	F	F/P	F/P	F/VP	F/VP	F/VP

E = EXCELLENT G = GOOD F = FAIR P= POOR VP = VERY POOR

Figure A-11. Coding form for 1984 version of Iowa offender rish assessment.

OFFENDER RISK ASSESSMENT
THE IOWA MODEL

X	Y	CURRENT OFFENSE SCORE (A)
2	3	Robbery/Attempted Robbery
2	3	Personal Larceny
2	3	Aggravated Burglary
2	3	Arson/Attempted Arson
1	3	Murder/Attempted Murder
1	3	Manslaughter
1	3	Kidnapping
1	3	Rape/Attempted Rape
1	3	Sodomy/Sex Offense
2	1	Burglary/Attempted Burglary
2	1	Selling Narcotics
2	1	Motor Vehicle Theft
2	1	Forgery/Bad Checks/Fraud
1	1	Aggravated Assault/Terrorism
1	1	Extortion
1	1	Weapons Crime (Violence)
1	1	Conspiracy (Violence)
1	1	Larceny/Stolen Property
1	0	Vandalism
1	0	Weapons Offense (No Violence)
1	0	Conspiracy (No Violence)
0	0	None of Above

X	Y	PRIOR VIOLENCE SCORE (B)
4	5	91+
2	3	11-90
0	0	0-10

X	Y	STREET TIME SCORE (C)
3	3	0-6 Years
2	2	6-11 Years
1	1	11-14 Years
0	0	14+ Years

X	Y	CRIMINAL HISTORY SCORE (D)
6	6	140+
3	5	41-139
1	1	16-40
0	0	0-15

X	Y	CURRENT ESCAPE SCORE (E)
3	4	Convicted
1	2	Charged Only
0	0	Not as Above

X	Y	SUBSTANCE ABUSE SCORE (F)
5	7	History of PCP Use
5	7	History of Non-Opiate Injections
5	7	History of Sniffing Volatile Substance
4	4	History of Opiate Addiction
3	4	History of Heavy Hallucinogen Use
2	1	History of Drug Problem
1	1	History of Opiate or Hallucinogen Use
1	1	History of Alcohol Problem
0	0	No History as Above

TOTAL SCORE = A + B + C + D + E + F

___ X-SCORE ___ Y-SCORE

SERIOUS OFFENDER CLASSIFICATION

Yes Current Conviction for Violent Felony
Yes Prior Conviction for Violent Felony in Last Five Years Street Time
Yes Prior Violence Score (Raw) = 35+
Yes Current Escape Conviction
Yes Substance Abuse Score (Y) = 7
No No Factor as Above

SAFETY RISK ASSESSMENT

Y-SCORE	X-SCORE 0-3	4-6	7-11	12+
0-8	VG	G	F	-
9+	-	F	P	VP

VIOLENCE RISK ASSESSMENT
(*Higher Rating for Serious Offender*)

Y-SCORE	X-SCORE 0-3	4-6	7+
0-8	E	VG	G
9-13	-	VG/P	G/P
14+	-	-	G/VP

E = EXCELLENT VG = VERY GOOD G = GOOD

F = FAIR P = POOR. VP = VERY POOR

Figure A-12. Coding form for 1985 version of Iowa offender risk assessment.

APPENDIX B

MAP OF MICHIGAN ADULT
CORRECTIONAL FACILITIES

<u>Figure B-1</u>. Map of facilities Operated by the Michigan Department of Corrections as of Dec. 31, 1983.

APPENDIX C

OFFENDER FILE WORKSHEETS

WORKSHEET

I) ID NUMBER ______________________

II) IF VS is OTHER, LIST DRUG ______________________

III) Criminal History

Arrest Date	Offense	Disposition	Dates Incarcerated	Person ( ) Offense

Prior Arrests ______________________

Prior Probations ______________________

Adult Jail ______________________

non-violent felony 0=no
w/disp. over 1yr. 1=yes ______________________

Juvenile Commitments ______________________

violent felony with 0=no
disp. over 1 year 1=yes ______________________

Adult Commitments ______________________

PAROLE VARIABLES

Parole Date = **2½ Years =**

Parole File

Violation Date	Arrest Date	Offense	Convicted	Misd. Felony

Recidivism Score =

If above is blank, are there any PV violations?

Police Rap Sheet

Arrest Date	Offense	Convicted	Misd. Felony

Recidivism Score =

# of Misd. Before Highest Recid. =
# of Nonviolent Felonies Before Recid =
# of Nonviolent Felonies After Recid =
# of Violent Felonies After Recid =

HIGHEST RECID SCORE =
(Enter Column 54)

If Rap Sheet Score Different, NOTE if HIGHER

APPENDIX D

DETAILED CODING INSTRUCTIONS

Details Regarding Coding and Recoding of Data

The following information is a detailed extension of material provided in Chapter IV (Methods).

Machine-Readable Data from Michigan Department

The Program Bureau of the Michigan Department of Corrections collected data from the criminal files of over 640 male offenders who had been released on parole during the 1980 calendar year. For individuals with multiple files, provisions were made to ship all discharged files to the coding site. This procedure aided in the reduction of missing data and permitted more thorough analysis of each offender's history. When information was not available from Department of Corrections files regarding prior criminal history, these data were obtained from state police records. A pilot study was included to identify discrepancies between variable definitions and coding procedures in the Iowa model, and data available in Michigan files. Coding formats were developed to ensure comparable study designs, when cross-validating the 1983 version of the Iowa Offender Risk Assessment model on the Michigan sample.

Using the Michigan codebook and instructions provided in Figure D-1 data were extracted from the files and coded by three coders. Narrative reports of arrests, summaries of court proceedings, psychological histories and pre-sentence investigations in each file were read to obtain information regarding criminal history, substance abuse history, age and current offense. State police "rap" sheets and parole files were reviewed by coders to determine whether or not sufficient evidence existed that charged individuals had actually committed the alleged offenses; that is, reported behavior was consistent with the charges for which arrests were made. Intercoder agreement was determined for each variable using randomly selected cases (selected biweekly) throughout the four-month data collection and coding period. Coding was not even commenced until the three coders had achieved intercoder agreement above 95 percent and this level of interrater agreement was maintained as a minimum throughout the data collection and coding phase. In all, 34 variables were coded for each case, including indicators of recidivism on parole over a 2 1/2 year follow-up period. These data (on computer tape), along with the "rough" offender file worksheets upon which they were based, comprised the sample for the present study.

Recoded and created variables from Michigan machine-readable data and worksheet information.

Offender file worksheets (Appendix C) were used to record "raw" variables for coding to complete a cross-validation of the 1983 version of the Iowa model on Michigan data (Murphy, 1985). First, a number of measures were extracted and used directly from the machine-readable data set, including: number of prior arrests, prior probations, prior adult jail terms, prior juvenile commitments, prior adult commitments, evidence of a juvenile felony arrest, property (non-violent) disposition greater than one year, person (violent) disposition greater than one year, felony history (coded "first offender"—yes/no), and number of major non-bondable misconducts (measures 2-6, 17-20 and 22 in Table 4.2).

Secondly, all prior felony charges, convictions and incarcerations were coded from the offender file worksheets. Regardless of the legal outcome, prior charges were coded using the numerical format displayed in Figure D-2. The recency of each charge was coded in street time extending backward in time from the arrest for the current offense. Charges which had occurred more than 99 months (street time) prior to the current offense arrest date were coded "99 months," since the exact "age" of any charge older than 99 months in street time was not critical for any analysis in the study. The numbers of charges coded in this manner were then grouped seperately according to whether or not they were for violent or non-violent felonies and, further, according to whether or not they had occurred in the last 12 months, 24 months, 36 months or 5 years of street time prior to the arrest date for the current offense. These resulting criminal history measures are numbered 7 through 16 in Table 4.2.

Charges listed on offender file worksheets were accompanied by titles of the offenses for which criminals were ultimately convicted. A typical example involving a larceny would indicate an original charge for "larceny over $100" or "larceny from a store" which was reduced to "simple larceny" or "larceny under $100" for conviction. When there was doubt as to whether or not a particular offense of conviction qualified as a felony, the list of "felonies of the same type," provided in Murphy's (1985) code book (Figure D-1) was consulted. The disposition of each charge was also provided in the worksheets (number of months on probation, amounts of fines or inclusive incarceration dates).

Computation of the number of years of street time since 14 years of age (measure 1 in Table 4.2) involved several steps. Initially, all periods of incarceration in each offenders history were coded. For lengthy incarcerations (over one year) the incarceration and release dates were both recorded in month- day-year format. Shorter periods such as 90 days in jail or four months in a juvenile facility were added together and then treated in the same way as lengthy incarcerations. Periods of incarceration were then computed using a series of SPSS:X (SPSS Inc., 1986) functions which convert dates to time periods. These were then summed and subtracted from age at parole (excluding the first fourteen years) to determine number of years of street time since 14 years of age. Other measures incorporating street time were computed in a similar manner.

The variable "multiple different charges with single arrest" (measure 21 in Table 4.2) was coded "1" if more than one charge was indicated for a given arrest and the charges were for very different offenses. In general terms, the list of "felonies of the same type" provided in Appendix D-1 was referred to; however, variations of burglary and larceny were considered similar rather than different offenses. To illustrate this point, an arrest for attempted burglary, larceny from a building and possession of burglar's tools would be coded

"0"; whereas, an arrest for robbery and attempted rape would be coded "1".

The operational measure of current offense from the current offense codes in the machine-readable data set was prepared by The State of Michigan Corrections Department. The Michigan offense list is provided in Appendix D-3.

Preliminary coding for measures of substance abuse history was quite involved. The substance abuse history information used to cross-validate the 1983 version of the Iowa model in Michigan had to be recoded. Specifically, all categories of substance abuse involving cocaine or marijuana had to be replaced with other categories for substance abuse history. In most cases no other form of substance abuse was indicated so a "0" code (No History as Above) was asigned. The first recoding procedure is illustrated in Figure D-4. For all cases which had been previously (during the 1983 Iowa model cross-validation) assigned codes of 2 (Cocaine), 5 (Marijuana) or 7 (Other) for history of problem use; or codes 2 (Cocaine) or 5 ("Occasional" use of Marijuana) for history of non-problem use, offender file worksheets were reviewed for other forms of substance abuse. Michigan Department of Corrections coders had been instructed to list all substances abused on worksheets, if more than one substance was involved. Often these listings included slang terms or names of chemicals which would be unfamiliar to anyone without an extensive knowledge of drug abuse. For this reason, a chapter on drug abuse in Achenbach (1982) was consulted to assist in categorizing these substances. The resulting list of definitions for substance abuse categories is provided in Figure D-5. An "update" function, available in Version 2.1 of SPSS:X (SPSS Inc., 1986), was used to replace all incompatible previous values for substance abuse history with these new values coded from the worksheets.

The operational measures in Table 4.4 were recoded from the Substance Abuse History Scale described in the previous paragraph. Modifications to produce these other measures are illustrated in Figure D-6. It should be noted that when the dichotomous "dummy" measures were coded (moving from most to least severe forms of substance abuse), these measures were hierarchically inclusive. As an example, the dichotomous variable 'prior abuse of some substance' is coded as a "0" for any substance abuse category less severe than "alcohol problem" and "1" for all other categories (2 through 9).

Operational measures related to age were among the least complex to compute and code. 'Age at first criminal arrest' (measure 2 in Table 4.5) was extracted and used directly from the machine-readable data set prepared by The Michigan Department of Corrections. 'Age at parole release' was computed from the combination of birth date and parole release date, using a function in SPSS:X (SPSS Inc., 1986) for converting dates to time intervals.

Preliminary coding for operational measures of recidivism on parole is discussed briefly in Chapter IV, relative to the first three measures in Table 4.6. Readers interested in details of coding instructions for The Michigan Parole Recidivism Score are directed to the last four pages in Figure D-1.

Basic Instructions

1. Go to master list and cross number off; check if more than one parole listed for 1980. If more than one parole listed, make sure file is for the first parole in time period.

2. If a person escaped and was convicted and the escape file is not in box, put file aside and note. If escape file is available but instant offense file is not, put aside and note.

3. After a person is coded, go to printout and list missing information next to name; also list any other discharge dates in the case of missing information.

4. If a file is not in the appropriate box, note on lot and box sheet.

5. When coding, please note the following:
   a. Put initials on top of coding sheet.
   b. Identify date coded on left-hand margin at top of page.
   c. Keep your coding sheets together.
   d. Number each code sheet started.
   e. At the end of the day, put ID's in numerical order by sheet number.

6. Instant offense refers to that crime the resident is serving on when he received his parole. Remember that escapes are not counted as instant offenses.

7. Unless specified, blanks should reflect missing data. Missing data may occur in two ways. First, the information is not available and second, the same source is conflicting and you can't determine the answer with reasonable accuracy. In most cases, missing data is designated as 9 or 99, therefore blanks should be ok'd by project director.

8. Secondary sources should be used to clarify or support information from the primary source. The only time a secondary source may be used in place of a primary source is if it is underlined in the manual.

9. If more than one file, check all of them for certain background information if necessary. However, for variables concerning the instant offense (i.e., marital status at time of offense) you must use instant offense file.

Source Instructions

In certain instances, secondary sources are identified. For example, if the presentence describes the background information but does not provide specific dates for those variables requiring them (i.e., age at first arrest), then supplement with the psych evaluation if available. Another situation would be if the presentence raises questions but does not provide enough information to make a decision. If the presentence says he was in trouble as a youth but does not say when or for what, then see if psych provides the missing information. One must designate those questions (i.e., age of first arrest) missing with appropriate code when a determination cannot be made. Also, juvenile information may be found in cases where more than one file is available.

Figure D-1. Michigan codebook and instructions.

Example: Using the previous criminal history example in conjunction with the specific risk designation category of "1 + prior conviction for a felony against persons in last 2 years street time."

1) Commitment date = 6-20-68

2) Subtract 2 years street time = 6-20-66

3) Subtract time incarcerated,
6-30-65 to 1-26-67 = 1 yr 7 mo = 11-20-64

Since the date of the previous robbery arrest (a person offense) was 4-26-65, the answer is yes. Use arrest date of prior's since conviction date is not always available.

Note: In many cases where no person offenses are checked, you only have to determine those nonperson categories. Refer to Appendix C for a list of comparable crimes.

When a special risk category refers to crimes instead of felonies, include misdemeanor arrests.

When a special risk category refers to TOTAL felonies, include the INSTANT OFFENSE.

Figure D-1. (Cont'd.)

INSTRUCTIONS FOR PAROLE VARIABLES

When determining parole behavior, use the following procedures:

1. Enter the parole date in the appropriate columns (48-53).
2. Flip through parole information for any pink or green sheets; also review any written correspondence; read all green sheets to determine the nature of the behavior; briefly review any pink sheets for criminal behavior.
3. List all arrests, violations.
4. Enter parole discharge or termination date. If absconder at end of file, code 999999.
5. Determine recidivism and other criminal history codes.
6. Add 2½ years to parole date and examine State Police rap sheet for this time period.
7. If no additions or changes, code 0 for variable.
8. If rap sheet would lead to a different recidivism score, then note appropriately (1 or 2).
9. Coding is completed.

NOTE: Remember, recidivism refers to actual behavior. For criminal behavior occurring outstate, make sure specific arrests are specified. Do not count "possible" arrests. When counting PV techs each must be listed on separate green sheets. In the case of multiple violations listed on one green sheet, then count as one. When counting misdemeanors, count each arrest. Finally, review recidivism instructions and bring all questionable cases to the project director.

Figure D-1. (Cont'd.)

NUMBER	COLUMN	VARIABLE	CODE
1	1-3	Study Number (Master List)	
2	4-9	Prison Number (Jacket Cover, Face Sheet)	
3	10-15	Corrected Date (Jaket Cover, Face)	MMDDYY
4	16	Race (Face Sheet)	0 = White 1 = Non-white
5	17-22	Birth Date (Face Sheet)	MMDDYY
6	23	Sex (Pre-sentence)	0 = Male 1 = Female
7	24	Single at Time of Crime (Never Married) (Pre-sentence, Face Sheet)	0 = No 1 = Yes
		Substance Abuse History	
8	25	History of Problem Use Note: If multiple problems, use rank order. For example, if subject has a problem with heroin and alcohol, code 1 for heroin. Evidence of injections would constitute problem. Problem use of marijuana refers to excessive use. For example, marijuana must be used on a daily or excessive basis. Other drugs must be used on a regular basis (e.g., hallucinogens). Regular use of heroin would constitute a problem. Statement of abuse is also a problem.	0. None 1. Heroin/Morphine 2. Cocaine 3. Hallucinogen 4. Glue 5. Marijuana 6. Alcohol 7. Other 8. Can't Determine
9	26	History of Non-Problem Use Note: If multiple drug use, use rank order. Code yes if ever used on nonregular basis. Examples: "Have used heroin twice"; Code marijuana only if used occasionally. (Pre-sentence, Psych Report)	0. None 1. Heroin 2. Cocaine 3. Hallucinogen 4. Glue 5. "Ocassional" Use of Marijuana 6. Can't Determine
		Prior Criminal History	
10	27-28	# of prior arrests	
11	29-30	# of prior probations	
12	31-32	# of prior adult jail	
13	33	Property disposition > 1 yr.	0 = No 1 = Yes

Figure D-1. (Cont'd.)

NUMBER	COLUMN	VARIABLE	CODE
14	34	# of prior juvenile commitments	
15	35	Person disposition > 1 yr.	0 = No 1 = Yes
16	36	# of prior adult commitments	

Note: Use worksheet for each case; Determine prior criminal history with pre-sentence criminal history section and rap sheet. Count each arrest, probation, etc., separately; Include juvenile arrests and commitments for status offenses and crimes. Exclude traffic offenses of a non-criminal nature such as speeding, no licence. Include DUIL, etc.
(Pre-sentence, RAP sheet)

NUMBER	COLUMN	VARIABLE	CODE
17	37-38	Age at first criminal arrest	99 = Can't Determine
18	39-40	Current Offense (Instant Offense)	Refer to Appendix A

Note: Instant Offense is the most serious offense a person is currently serving on. Refer to Appendix A for appropriate code. Violent offenses are more serious than nonviolent offenses. For similar offenses, use longest minimum. If a person is serving on a property crime that is assaultive in nature or multiple charges that include an assaultive offense, ask project director how to classify. Also, read B & E to determine aggravation.
(Jacket Cover, Pre-sentence)

NUMBER	COLUMN	VARIABLE	CODE
19	41	First Offender	0 = No 1 = Yes

Note: Code yes if no prior felony arrest as a juvenile or adult.

NUMBER	COLUMN	VARIABLE	CODE
20	42	Serving on current escape or jail break	0 = No 1 = Yes

Note: Must have an escape sentence

NUMBER	COLUMN	VARIABLE	CODE
21	43	Major Non-Bondable Misconduct (Misconduct Reports)	0 = None 1 = One 2 = 2 or More

Note: Flip through file and use misconduct hearing reports. Major misconducts are listed in Appendix D.

Special Risk Factors

NUMBER	COLUMN	VARIABLE	CODE
22	44	Risk Factor 1	0-8

Figure D-1. (Cont'd.)

NUMBER	COLUMN	VARIABLE	CODE
		Note: For Variables 22 through 25, use worksheet. If V22 is yes, terminate coding. If V22 is no, continue. Do not leave V22 blank. See worksheet for instructions.	
23	45	Risk Factor 2	0-5 9 = Not Applicable
24	46	Risk Factor 3	1-4 9 = Not Applicable
25	47	Risk Factor 4	1-3 9 = Not Applicable
		Note: Refer to instruction sheet for distinctions between crimes, felonies, total offenses and prior offenses.	
		PAROLE VARIABLES	
26	48-53	Date of 1980 parole	MMDDYY
		Note: Use date on parole board order for parole.	
27	54	Recidivism Score (Behavioral Analysis) 1 = No Illegal Activities 2 = Technical Violation or Absconder ONLY (no other illegal behavior) 3 = Misdemeanor 4 = Nonviolent Felony 5 = Violent Felony	1 - 5
		Note: Exclude traffic viiolations; ask project director on all questionable cases; refer to recidivism handout.	
28	55-60	Date of Recid Score	MMDDYY
		Note: If recid score is 1, use discharge date If recid score is 2, use first PV violation date If recid score is 3, use first misdemeanor date If recid score is 4 or 5, use felony violation date.	
		The following 2 variables refer to separate criminal violations occurring before recidivism score.	
29	61	Number of Misdemeanors	0 - 3

Figure D-1. (Cont'd.)

NUMBER	COLUMN	VARIABLE	CODE
30	62	Number of Nonviolent Felonies	
		Note: 1) Code number of violations occurring before Rec. Score; 2) Code the behavior. (Up to 3 each).	
		Post Recidivism: The following 2 variables refer to felonies committed after recidivism score.	
31	63	Number of nonviolent felonies committed after recid. score.	0 - 3
32	64	Number of violent felonies committed after recid. score.	
33	65	Returned to prison	0 = No 1 = Yes
34	66-71	Date of parole discharge or incarceration. (From parole file)	MMDDYY 999999 - abscond
		Note: Use date of confinement if in jail immediately prior to discharge or return to prison.	
35	72	Rap Sheet (2-1/2 yr. follow-up)	0 = No 1 = Yes, Higher 2 = Yes, Lower
		Note: Code yes only if discrepancy results in a higher or lower recid score.	
36	73	Conviction for Recidivism Score	1 = No Felony 2 = Yes Convicted 3 = Not Convicted
37	74	Coder I.D.	
38	75	Evidence of Juvenile Felony	0 = No 1 = Yes

Figure D-1. (Cont'd.)

APPENDIX B

PERSON FELONIES (VIOLENT)

OFFENSE

Homicide: first degree murder
Homicide: second degree murder
Homicide: manslaughter
Homicide: negligent homicide
Rape - Criminal Sexual Conduct
Sodomy
Extortion
Abduction - Kidnapping
Robbery Armed and Unarmed
Larceny from Person
Attempt to Murder or Commit Robbery
All Assaults and Assaults with Intent
Arson: burning dwelling house
Offenses Against Children: torture
Offenses Against Children: cruelty
Offenses Against Children: exposure
Indecent Liberties with Child
Gross Indecency

HIGH RECIDIVISM OFFENSES

Burglary
Motor Vehicle Theft
Forgery
Bad Checks
Robbery

Assault (Attempt to commit murder, serious injury, felonious assault and assault with intent to commit harm or injury)

PERSON MISDEMEANORS

Assault and Battery
Aggravated Assault
Assaulting Police Officer

Figure D-1. (Cont'd.)

APPENDIX C

FELONIES OF THE SAME TYPE
Murder, manslaughter, feticide and attempts, felonious assault, assault with intent to harm or maim.
Rape, attempted rape, criminal sexual conduct I and III, assault with intent to rape or commit criminal sexual conduct, sodomy, gross indecency, incest, other sex offenses.
Kidnapping, conspiracy and attempts.
Robbery, attempted robbery, assault with intent to rob, extortion, larceny from a person.
Burglary, attempted burglary, entering without breaking, possession of burglar's tools.
Larceny from building, by conversion, false pretenses, receiving and concealing, larceny over $100.
U.D.A.A., All motor vehicle offenses.
Embezzlement.
Forgery, uttering and publishing, check offenses, possession of counterfeit notes.
Arson, vandalism (malicious destruction), explosives offenses, bomb threat.
Weapon offenses (CCW, attempted CCW, etc.).
Drug offenses (sale and use).
Alcohol offenses (drunk driving).
Pandering, pornography.
Escape, Jailbreak.
Bribery, perjury, obstruction.
Neglect, abandonment, child offenses.

Figure D-1. (Cont'd.)

Appendix D

NONBONDABLE MAJOR MISCONDUCTS

Assault and Battery
Attempt to Escape
Escape
Fighting
Homicide
Incite to Riot or Strike
POssession of Dangerous Contraband
Rioting or Striking
Sexual Assault
Threatening Behavior

Figure D-1. (Cont'd.)

RECIDIVISM SCORE

This scale is a behavioral index of the inmate's most SERIOUS behavior while on parole. For example, if a parolee had only committed a minor technical violation on parole and nothing else, he would be coded a two on this scale. If he had committed both a misdemeanor (three) and a violent felony (five) while on parole, he would receive a "five". The coding criteria for this scale should be based upon written descriptions from police and/or agent records whenever possible. The criteria do not rest upon arraignments nor convictions but reflect as closely as possible the actual reported behavioral description of the man's activity.

We are interested in behavior on parole, not legal dispositions. It is necessary for the coder to review the file carefully. If a person is arrested during parole, examine the police report and/or sheet and decide if enough evidence exists to determine guilt.

I. General definitions of recidivism categories.

1) No criminal behavior: No arrests for criminal behabior. Only arrests which are mistakes and the person is released.

2) PV Technical and Absconder: No criminal behavior but cited for a PV or he absconds. No other indicators of criminal behavior.

3) Misdemeanor: Arrest and behavior is for a misdemeanor such as drunk and disorderly, petty larceny, etc.

4) Non-Violent Felony: Behavior and evidence constitutes a felony via arrest.* If convicted of a non-violent felony that is actually violent, it is a violent Rec. 2.

5) Violent Felony: Behavior in arrest constitutes violence and evidence supports it (i.e., eyewitness, etc.). Violence is defined by intimidation either verbally or physically.

---

* Under certain circumstances, arrests may not occur for serious felony involvement. Past examples have included a parolee shot during the commission of a felony. However, instances where an arrest does not occur are very infrequent and should be verified by the project director. It is more common for a charge not to reflect behavior. If a felony involved intimidation, then violent felony is appropriate regardless of charge. In a few cases concerning male parolees, the failure to prosecute a rape has resulted in the arrest for a related non-violent felony (i.e., Breaking & Entering). If a rape occurred you would be expected to code 5 and not a 4.

Figure D-1. (Cont'd.)

II. Specific Examples:

1) No criminal behavior: A person is on parole for a year. He is arrested for robbery armed and later released. The file contains no evidence to indicate his involvement, therefore, he is coded a 1. The most common case in this category is the person that is never arrested and has no technical violations on parole.

2) PV Tech./Absconder A person is seen in a bar by his agent and is cited for a technical violation. Any parole violations that do not constitute criminal behavior belong in this category. If a person absconds upon release and his file indicates no further activities of a criminal nature, then he would be coded a 2.

3) Misdemeanor: An offender is arrested for disorderly conduct, assault and battery, etc. If the investigator feels that he was involved in the incident, he would be coded a 3.

4) Non-Violent Felony: For the most part, non-violent felonies are determined by the arresting charge and evidence. It is important to realize that we are not interested in plea bargaining and other legal maneuvers. For instance, if a person is arrested for selling heroin and the description supports the case but he pleas to a misdemeanor of use, then he is coded a 4. If a person commits a series of misdemeanors and one non-violent felony, he is considered a 4. A person is coded for his most serious behavior on parole. An important issue to be aware of is the case where a person commits a non-violent felony and is given probation and then later commits a violent felony. He would be a 5.

5) Violent Felony: A violent felony is the most serious recidivism score a person can receive regardless of degree. For instance, if a person commits a robbery and then later commits a rape, the robbery is sufficient to code as a 5. A common problem occurs when a person is arrested for robbery armed and pleas to larceny. The person is a 5 not a 4 if the description supports intimidation. A more serious coding problem occurs when a person commits a crime and is discharged before the trial. This happens more frequently with violent crimes than the other categories. Regardless of discharge, he is a if the evidence supports the decision.

III. Common Problems Encountered

In most cases, past experience has shown that the descriptions provide sufficient information to make a clear decision on recidivism. However, there are certain problems that appear to

Figure D-1. (Cont'd.)

cause confusion and require some deliberation. Therefore, the following list focuses on common and frequent issued concerning recidivism.

1) Always code his most <u>serious</u> behavior <u>not</u> necessarily his first crime.

2) When a person is convicted of a property crime and is given probation, make sure he doesn't commit a violent felony later. In that case he would be given a 5, not a 4.

3) Frequently, a felony does not go to trial until a person is on parole for various reasons:

   a) <u>Plea bargain</u>: Ignore the plea bargain if the original charge <u>and</u> supporting evidence indicates otherwise.

   b) <u>Pending trial, parole sheet says "let the courts decide"</u>. Many times a parole decision will state that he will be continued on parole while the trial is pending. Consequently, he may be discharged before trial. The coders are to ignore these parole decisions. If the witnesses, descriptions, etc. support a felony decision, he is coded accordingly with the recidivism definitions.

   c) <u>Waiting in jail pending court date, discharged off parole</u>: Ignore and use his behavior to decide.

   d) <u>Absconder, wanted for a felony</u>: Again, use the description of his behavior to determine if he committed a felony.

   Points a, b, c, and d above all emphasize one point: We are <u>not interested in legal or administrative decisions</u> but the behavior involved.

4) <u>Domestic Disputes</u>: These are one of the most difficult cases to resolve. The rule of thumb is <u>not</u> to count domestic disputes if they are a case of minor fighting. For instance, if a parolee has a clean record on parole but her spouse calls police and she is arrested and released, she would normally be counted as a 1 (no criminal activity). The rationale for this is that a large number of our population experience domestic problems <u>before</u> and <u>after</u> prison. More importantly, there are usually two sides to the story. Consequently, an Assault and Battery for shoving or pushing should be examined carefully. The only traditional exceptions to this is where serious bodily injury occurs. In that case, it is either an Assault and Battery or a felony depending on the arrest.

<u>Figure D-1</u>. Cont'd.)

5) AWOL, traffic tickets, prior fugitive warrants, and prior warrants are to be ignored. We are interested in parole criminal behavior.

6) In certain instances, a parole agent is sure of the parolee's guilt but the charges are dropped. The agent may state that the victim called him and he has been threatened. The parolee should be coded according to the behavior.

7) In instances where the evidence is not clear and there is no basis for making a decision, then the general rule of thumb is to code in favor of the parolee. A case was noted where a parolee was arrested for UDAA. Yet the owner of the vehicle supported the parolee's version of borrowing the car. In this case, the code should be in favor of the parolee. (Do not presume guilt but be aware that there are situations where the circumstances are clear but the charges are dropped.)

8) The general rule of thumb for category #2 (technical violation) is to rely on a green sheet in the file. Do not presuppose the violations of parolees. The exception may be with those parolees with special conditions. For instance, the parolee is not to use drugs but is caught using them. Because of program guidelines, agents are not required to formally reprimand them.

9) Those incidences where a person absconds and is arrested in another state for a felony but no description is provided may require that recidivism be left blank.

10) A source of information in files that may assist in determining recidivism is the Parole Board hearings where the arresting officer, agent, etc., reviews the circumstances.

In most cases, the problems above should not be encountered. Past experience has shown that a good file leads to little confusion. Hopefully, where questions remain, the above discussion will be of assistance.

Figure D-1. (Cont'd.)

Violent Offense	Prior Offense Code	Felony Offense Title
*	01	Murder
*	02	Attempted Murder
*	03	Rape
*	04	Kidnapping for Ransom
*	05	Aggravated Robbery
*	06	Aggravated Burglary
*	07	Arson of a Dwelling
*	08	Selling Narcotics to Minors
*	09	Voluntary Manslaughter
*	10	Attempted Rape
*	11	Sodomy
*	12	Kidnapping
*	13	Robbery
*	14	Larceny from a Person
*	15	Felony Assault
*	16	Terrorism
*	17	Arson
*	18	Involuntary Manslaughter
*	19	Attempted Robbery
*	20	Extortion
*	21	Going Armed with Intent
	22	Escape
	23	Jailbreak
*	24	Aggravated Assault
*	25	Attempted Arson
*	26	Conspiracy to Commit a Violent Felony
	27	Burglary
	28	Motor Vehicle Theft
	29	Forgery
	30	Selling Narcotics (opiates or cocoaine)
	31	Larceny
	32	Stolen Property
	33	Vandalism
	34	Bad Checks/Fraud
	35	Weapons Offense
	36	Conspiracy to Commit a Non- Violent Felony (above)
	37	All Other Offenses, e.g., lascivious acts, selling drugs, drunken driving.

Figure D-2. Offense-specific coding for prior felonies

Offense	Code
Homicide	01
Attempted Murder	02
Assault With Intent to Murder	03
CSC, Rape	04
Attempt to Assault to CSC, Rape	05
Abduction, Kidnapping	06
Robbery Armed	07
Robbery Unarmed	08
Attempted Robbery	09
Assault With Intent to Rob	10
Other Assaults (Felonious, Assault to Maim, etc.)	11
Sodomy	12
Gross Indecency	13
Children: Torture, Cruelty, Expose	14
Indecent Liberties With Child	15
Extortion	16
Larceny from Person (Assaultive)	17
Larceny from Person (Non-Assaultive)	18
Arson - Dwelling Only	19
Arson - Building	20
Aggravated Burglary	21
Burglary	22
Larceny (Includes Larceny Auto)	23
Auto Theft	24
Forgery - Uttering & Publishing	25
Embezzlement	26
Bad Checks	27
Malicious Destruction	28
Drugs	29
Alcohol Related	30
Sex Offenses (Other)	31
Children Offenses (Other)	32
Other Offenses	33

Figure D-3. Michigan current offense codes.

Substance Abuse Scale Used in This Study

History of

(A)	PCP Use
(B)	Sniffing Volatile Substance
(C)	Opiate Addiction
(D)	Heavy Hallucinogen Use
(E)	Drug Problem
(F)	Opiate or Hallucinogen Use
(G)	Alcohol Problem
(O)	No History of Above

1983 Version

Current Code	History of Problem Use	Current Code	History of Non-Problem Use
(O)	0. None	(O)	0. None
(C)	1. Heroine/Morphine	(F)	1. Heroine
(n/a)	2. Cocaine	(n/a)	2. Cocaine
(D)	3. Hallucinogen	(F)	3. Hallucinogen
(B)	4. Glue	(B)	4. Glue
(n/a)	5. Marijuana	(n/a)	5. "Occasional" Use of Marijuana
(G)	6. Alcohol	(missing)	6. Can't Determine
(A or E)	7. Other		
(missing)	8. Can't Determine		

Figure D-4. Substance abuse history: Modification of codes for 1983 version of Iowa model.

Category	Substances Included ("slang" terms added)
History of PCP Use	Phencyclidine, "angel dust", "crystal", "Pea Ce Pill."
History of Non-Opiate Injections	"Shooting" drugs other than those included as opiates, below.
History of Sniffing Volatile Substance	Sniffing glue or other organic solvents such as acetone or benzene contained in glue.
History of Opiate Addiction	Addiction to heroin, morphine, paregoric, codeine, opium; or to synthetic opium-like drugs such as methadone, pentazocaine (Talwin, or "T"s), and Tripelenamine (Pyribenzamine, or "Blues"). Indications of frequent or regular "mainlining" of "H", "Horse", "junk", "joy powder", "skag", "speedballs".
History of Heavy Hallucinogen Use	Indications of frequest or regular use of LSD (Lysergic Acid Diethylamide), Mescaline (peyote) or Psilocybin ("mushrooms").
History of Drug Problem	Indications of frequent or regular use of Amphetamines, including benzedrine ("bennies") and dexedrine ("dexies"); or Barbiturates, including secobarbital, pentobarbital and phenobarbital. Other slang terms for Amphetamines include "speed", "pep pills" and "uppers". Other terms for Barbiturates include "barbs", "goofballs" and "candy". Other substances considered under drug problem are Methylphenidate (Ritalin), Sleeping Pills (methaqualone, ethchlorvynol, doriden, placidyl, quaalude) and "minor" tranquilizers such as librium, valium and equanil.
History of Opiate or Hallucinogen Use	Indications of infrequent or only occasional use of opiates or hallucinogens, as they are defined above.
History of Alcohol Problem	Indications of heavy, frequent and disruptive use of alcohol (i.e., arrests for public drunk and disorderly conduct, driving while intoxicated with liquor, etc.).
No History as Above	No substance abuse indicated, as defined above.

Note: During the development of these definitions, frequent reference was made to Chapter 14 of T.M. Achenbach (1982), Developmental psychopathology (2nd ed.), New York: John Wiley & Sons.

Figure D-5. Definitions of Substance Abuse Categories

Current Coding History of:	Collapsed Coding
9. PCP Use	4. Hardest Chemicals Used
7. Sniffing Volatile Substance	4. Hardest Chemicals Used
6. Opiate Addiction	3. Problem Opiate/Hallucingen Use
5. Heavy Hallucinogen Use	3. Problem Opiate/Hallucingen Use
4. Drug Problem	2. Some Abuse of Chemicals
3. Opiate or Hallucinogen Use	2. Some Abuse of Chemicals
2. Alcohol Problem	1. Alcohol Problem Only
0. No History of Above	0. No History As Above

Current Coding History of:	Dichotomous "Dummy Interval Coding"
9. PCP Use	PCP or Sniffing
7. Sniffing Volatile Substances	PCP or Sniffing
6. Opiate Addiction	Serious Problem Use of Chemical Substance
5. Heavy Hallucinogen Use	Serious Problem Use of Chemical Substance
4. Drug Problem	Abuse of Some Form of Chemical Substance
3. Opiate or Hallucinogen Use	Abuse of Some Form of Chemical Substance
2. Alcohol Problem	Abuse of Some Substance
0. No History as Above	

Figure D-6. Substance abuse history: Modification of codes to produce other measures of substance abuse history.

APPENDIX E

MATRICES USED IN COMPUTATION OF MCR AND IOC

Optimal cut-point for minimizing loss function = .308, MCR[a] = .03, IOC[b] = 0.6%

		Predicted parole outcome: Arrest for violent felony	Predicted parole outcome: No Arrest for violent felony	
Observed parole outcome	Arrest for violent felony	1	31	32 10.5%
	No arrest for violent felony	0	272	272 89.5%
		1 0.3%	303 99.7%	304* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-1. Parole prediction outcome (construction subsample I) for arrest for violent felony, using logistic regression model number 1.

Optimal cut-point for minimizing loss function = .308, MCR[a] = .02, IOC[b] = 0.5%

		Predicted parole outcome: Arrest for general felony	Predicted parole outcome: No Arrest for general felony	
Observed parole outcome	Arrest for general felony	1	39	40 13.0%
	No arrest for general felony	1	267	268 87.0%
		2 0.6%	306 99.4%	308* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-2. Parole prediction outcome (cross-validation subsample II) for arrest for violent felony, using logistic regression model number 1.

Optimal cut-point for minimizing loss function = .542, MCR[a] = .36, IOC[b] = 17.1%

		Predicted parole outcome		
		Arrest for general felony	No Arrest for general felony	
Observed parole outcome	Arrest for general felony	62	61	123 40.5%
	No arrest for general felony	27	154	181 59.5%
		89 29.3%	215 70.7%	304* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-3. Parole prediction outcome (construction subsample I) for arrest for general felony, using logistic regression model number 2.

Optimal cut-point for minimizing loss function = .542, MCR[a] = .17, IOC[b] = 8.2%

		Predicted parole outcome: Arrest for general felony	Predicted parole outcome: No Arrest for general felony	
Observed parole outcome	Arrest for general felony	40	94	134 43.5%
	No arrest for general felony	23	151	174 56.5%
		63 20.5%	245 79.5%	308* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-4. Parole prediction outcome (cross-validation subsample II) for arrest for general felony, using logistic regression model number 2.

Optimal cut-point for minimizing loss function = .475, MCR[a] = .35, IOC[b] = 16.9%

Predicted parole outcome

		Arrest for general felony	No Arrest for general felony	
Observed parole outcome	Arrest for general felony	69	54	123 40.5%
	No arrest for general felony	38	143	181 59.5%
		107 35.2%	197 64.8%	304* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-5. Parole prediction outcome (construction subsample I) for arrest for general felony, using logistic regression model number 3, excluding marital status and race as predictors.

Optimal cut-point for minimizing loss function = .475, MCR[a] = .12, IOC[b] = 6.0%

		Predicted parole outcome		
		Arrest for general felony	No Arrest for general felony	
Observed parole outcome	Arrest for general felony	44	90	134 43.5%
	No arrest for general felony	36	138	174 56.5%
		80 26.0%	228 74.0%	308* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-6. Parole prediction outcome (cross-validation subsample II) for arrest for general felony, using logistic regression model number 3, excluding marital status and race as predictors.

Optimal cut-point for minimizing loss function = .458, MCR[a] = .03, IOC[b] = 0.5%

		Predicted parole outcome		
		Arrest for violent felony	No Arrest for violent felony	
Observed parole outcome	Arrest for violent felony	1	39	40 13.0%
	No arrest for violent felony	0	268	268 87.0%
		1 0.3%	307 99.7%	308* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-7. Parole prediction outcome (construction subsample II) for arrest for violent felony, using logistic regression model number 4.

Optimal cut-point for minimizing loss function = .458, MCR[a] = .03, IOC[b] = 0.6%

		Predicted parole outcome: Arrest for general felony	Predicted parole outcome: No Arrest for general felony	
Observed parole outcome	Arrest for general felony	1	31	32 10.5%
	No arrest for general felony	0	272	272 89.5%
		1 0.3%	303 99.7%	304* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-8. Parole prediction outcome (cross-validation subsample I) for arrest for violent felony, using logistic regression model number 4.

Optimal cut-point for minimizing loss function = .475, MCR[a] = .30, IOC[b] = 14.4%

		Predicted parole outcome		
		Arrest for general felony	No Arrest for general felony	
Observed parole outcome	Arrest for general felony	80	54	134 43.5%
	No arrest for general felony	53	121	174 56.5%
		133 43.2%	175 56.8%	308* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-9. Parole prediction outcome (construction subsample II) for arrest for general felony, using logistic regression model number 5.

Optimal cut-point for minimizing loss function = .475, MCR[a] = .17, IOC[b] = 8.3%

		Predicted parole outcome		
		Arrest for general felony	No Arrest for general felony	
Observed parole outcome	Arrest for general felony	70	53	123 40.5%
	No arrest for general felony	72	109	181 59.5%
		142 46.7%	162 53.3%	304* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-10. Parole prediction outcome (cross-validation subsample I) for arrest for general felony, using logistic regression model number 5.

Optimal cut-point for minimizing loss function = .425, MCR[a] = .41, IOC[b] = 20.2%

		Predicted parole outcome: Arrest for general felony	Predicted parole outcome: No Arrest for general felony	
Observed parole outcome	Arrest for general felony	107	27	134 43.5%
	No arrest for general felony	67	107	174 56.5%
		174 56.5%	134 43.5%	308* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-11. Parole prediction outcome (construction subsample II) for arrest for general felony, using logistic regression model number 6, excluding marital status and race as predictors.

Optimal cut-point for minimizing loss function = .425, MCR[a] = .22, IOC[b] = 10.4%

		Predicted parole outcome: Arrest for general felony	Predicted parole outcome: No Arrest for general felony	
Observed parole outcome	Arrest for general felony	89	34	123 40.5%
	No arrest for general felony	92	89	181 59.5%
		181 59.5%	123 40.5%	304* 100.0%

* N of cases varies from the total available in subsamples because only cases with nonmissing values for every operational measure are included in the analysis.
a Mean Cost Rating
b Improvement Over Chance

Figure E-12. Parole prediction outcome (cross-validation subsample I) for arrest for general felony, using logistic regression model number 6, excluding marital status and race as predictors.

LIST OF REFERENCES

LIST OF REFERENCES

Achenbach, T.M. (1982). Developmental psychopathology. (2nd ed.). New York: John Wiley & Sons.

Aiken, L. R. (1979). Psychological testing and assessment (3rd ed.). Boston, MA: Allyn & Bacon.

Allen, M.J. & Yen, W.M. (1979). Introduction to measurement theory. Monterey, CA: Books/Cole.

American Psychological Association. (1981). Ethical principles of psychologists. American Psychologist, 36, 633-638

American Psychological Association. (1983). Publication Manual of the APA (Rev. Ed.); Washington, B.C., APA

American Psychological Association. (1978). Report of the task force on the role of psychology in the criminal justice system. American Psychologist, 33, 1099-1113.

Anastasi, A. (1976). Psychological testing (4th ed.). New York: MacMillan.

Andrews, F. M., Klem, L., Davidson, T. D., O'Malley, P. M., & Rodgers, W. L. (1981). Guide for selecting statistical techniques for analyzing social science data (2nd ed.). Ann Arbor, MI: Institute for Social Research.

Anthony, A., & Oldroyd, R. J. (1979). Predictive validity of the history/risk assessment for parolees (NCJ No. 64267). Washington, D. C.: National Criminal Justice Reference Service.

Astone, N. A. (1981). Variables affecting parole outcomes. Southern Journal of Criminal Justice, 6, 7-38.

Baird, C. (1981). Probation and parole classification: The Wisconsin model. Corrections Today, 43(3), 36-41.

Berry, W. D., & Feldman, S. (1985). Multiple regression in practice. Beverly Hills, CA: Sage.

Blackmon, L. S. (1983). Reliability and validity of the Megargee typology: An investigation using a female inmate population (Doctoral dissertation, The George Washington University, 1982). Dissertation Abstracts International, 43, 3044B.

Bonham, G., Janeksela, G., Bardo, J., & Iacovetta, R. (1984). Predicting parole outcome via discriminant analysis. Justice Quarterly, 1, 329-341.

Booth, R.J. (1980). Classification of prison inmates with the MMPI: An extension and validation of the Megargee typology (Doctoral dissertation, Brigham Young University, 1980). Dissertation Abstracts International, 41, 1493B.

Boudouris, J. (1983). The recidivism of releases from the Iowa State Penitentiary at Fort Madison. Des Moines, IA: Division of Adult Corrections.

Bruce, A., Harno, A., Landesco, J., & Burgess, E. (1928). The working of the indeterminate sentence law and the parolee system in Illinois. Springfield, IL: Illinois Parole Board.

Chaiken, J., & Chaiken, M. (1982a). Varieties of criminal behavior. Santa Monica, CA: RAND.

Chaiken, J., & Chaiken, M. (1982b). Varieties of criminal behavior: Summary and policy implications. Santa Monica, CA: RAND.

Cline, H. F. (1979). Criminal behavior over the life span. In O.G. Brim & J. Kagan (Eds.), Constancy and change in human development. Cambridge: Harvard University Press.

Collins, L. M., Cliff, N., Cudeck, R.A., McCormick, D. J., & Zatkin, J. L. (1983). Patterns of crime in a birth cohort. Multivariate Behavioral Research, 18, 235-258.

Cormier, R. B. (1981). Research notes: Canadian recidivism index. Canadian Journal of Criminology, 23, 103-104.

Cox, D.R. (1970). The analysis of binary data. London: Chapman and Hall.

Cureton, E. E. (1950). Validity, reliability and baloney. Educational and Psychological Measurement, 10, 94-96.

Dean, C. W. (1968). New directions for parole prediction research. Journal of Criminal Law, Criminology and Police Science, 59, 214-219.

Dietz, C. (1985). Parole: Crucial to our criminal justice system. Corrections Today, 47(3), pp. 30, 32.

Dinitz, S., & Conrad, J. P. (1978, March). Thinking about dangerous offenders. Criminal Justice Abstracts, 99-130.

Dobson, A.J. (1983). An introduction to statistical modelling. New York: Chapman & Hall.

Duncan, O. D., Ohlin, L. E. & Reiss, A. J., Jr. (1953). Formal devices for making selection decisions. American Journal of Sociology, 58, 573-584.

Edinger, J. D. (1978). A multidimensional-multivariate approach to personality: An empirical test within a correctional setting (Doctoral dissertation, Virginia Commonwealth University, 1977). Dissertation Abstracts International, 38(10), 5012B.

Edinger, J. D. (1979). Cross validation of the Megargee MMPI typology for prisoners. Journal of Consulting and Clinical Psychology, 47, 234-242.

Edinger, J. D., Reuterfors, D., & Logue, P. E. (1982). Cross-validation of the Megargee MMPI typology: A study of specialized inmate populations. Criminal Justice and Behavior, 9, 184-203.

Elliott, D. S., & Huizinga, D. (1984). The relationship between delinquent behavior and ADM problem behaviors. Boulder, CO: Behavioral Research Institute.

Engelman, L. (1983). PLR: Stepwise logistic regression. In W.J. Dixon & M.B. Brown (Eds.), BMDP Statistical Software (rev. ed.) (pp.330-344). Los Angeles: University of California Press.

Ensminger, M. E., Kellam, S. G., & Barnett, R. R. (1983). School and family origins of delinquency: Comparisons by sex. In K. T. Van Dusen & S. A. Mednick (Eds.), Prospective studies of crime and delinquency (pp. 73-97). Boston: Kluwer-Nijhoff.

Farrington, D. P. (1978). The family backgrounds of agressive youths. In L. Hersov, M. Berger & D. Shaffer (Eds.), Aggression and antisocial behaviour in childhood and adolescence. Oxford: Pergamon.

Farrington, D. P. (1982). Longitudinal analyses of criminal violence. In M. E. Wolfgang & N. A. Weiner (Eds.), Criminal Violence (pp. 171-200). Beverly Hills, CA: Sage.

Farrington, D. P. (1983). Offending from 10 to 25 years of age. In K. T. Van Dusen & S. A. Mednick (Eds.), Prospective studies of crime and delinquency (pp. 17-38). Boston: Kluwer-Nijhoff.

Farrington, D. P., Berkowitz, L., & West, D. J. (1982). British Journal of Social Psychology, 21, 323-333.

Farrington, D. P., & West, D. J. (1981). The Cambridge study in delinquent development. In S. A. Mednick & A. E. Baert (Eds.), Prospective longitudinal research. Oxford: Oxford University Press.

Federal Bureau of Investigation. (1972). Uniform crime reports. Washington, D. C.: U.S. Government Printing Office.

Fischer, D. (1980). Recidivism research in Iowa. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

Fischer, D. (1983a). Better public protection with fewer inmates? Corrections Today, 45(6), 16-20.

Fischer, D. (1983b). Selective incapacitation of potentially violent adult offenders. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

Fischer, D. R. (1985). Prediction and incapacitation: Issues and answers. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

Fischer, D., & Stageberg, P. (1983). Policy relevance in criminal justice research. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

Forst, B., Rhodes, W., Dimm, J., Gelman, A., & Mullin, B. (1983). Targeting federal resources on recidivists: An empirical view. Federal Probation, 47(2), 10-20.

Fowler, L. T. (1983). Classification and prediction: Improving on chance. Corrections Today, 45(6), 44-47.

Gearing, M. L., II. (1979). The MMPI as a primary differentiator and predictor of behavior in prison: A methodological critique and review of recent literature. Psychological Bulletin, 86, 929-963.

Gendreau, P., Irvine, M., & Knight, S. (1973). Evaluating response set styles on the MMPI with prisoners: Faking good adjustment and maladjustment. Canadian Journal of Behavioural Science, 5, 183-194.

Gendreau, P., & Leipciger, M. (1978). The development of a recidivism measure and its application in Ontario. Canadian Journal of Criminology, 20, 3-17.

Gendreau, P., Madden, P., & Leipciger, M. (1980). Predicting recidivism with social history information and a comparison in their predictive power with psychometric methods. Canadian Journal of Criminology, 22, 328-336.

Glaser, D. (1954). A reconsideration of some parole prediction factors. American Sociological Review, 19, 335-341.

Glaser, D. (1964). The effectiveness of a prison and parole system. Indianapolis, IN: Bobbs-Merrill.

Glueck, S., & Glueck, E. (1950). Unraveling juvenile delinquency. Cambridge, MA: Harvard University Press.

Godfrey, E. A., & Schulman, R. E. (1972). Age and a group test battery as predictors of types of crime. Journal of Clinical Psychology, 28, 339-342.

Goodwin, D. W., & Guze, S. B. (1984). Psychiatric Diagnosis (3rd ed.). New York: Oxford University Press.

Gottfredson, D. M. (1967). Assessment and prediction methods in crime and delinquency. In U.S. Task Force on Juvenile Delinquency (Eds.), Task force report: Juvenile delinquency and youth crime (Appendix K, pp. 171-187). Washington, D.C.: U.S. Government Printing Office.

Gottfredson, D., Wilkins, L., & Hoffman, P. (1978). Guidelines for parole and sentencing. Lexington, MA: Lexington Books.

Gottfredson, S. D., & Gottfredson, D. M. (1980). Screening for risk: A comparison of methods. Criminal Justice & Behavior, 7, 315-330.

Gottfredson, S. D., & Gottfredson, D. M. (in press). Accuracy of prediction models. In Panel on Research in Criminal Careers (Eds.), Criminal careers and "career criminals": Vol. 2. Washington, D.C.: National Academy of Sciences Press.

Gough, H. G. (1962). Clinical vs. statistical prediction in psychology. In L. Postman (Ed.), Psychology in the making (pp. 526-584). New York: Knopf.

Greenwood, P. W. (1982). Selective incapacitation. Santa Monica, CA: RAND.

Haig, M. (1981, December 7). Crippling the long arm of the law. Macleans, p. 10.

Hayes, W.L. (1981). Statistics (3rd ed.). New York: Holt, Rinehart & Winston.

Hildebrand, D. K., Laing, J. D., & Rosenthal, H. (1977). Analysis of ordinal data. Beverly Hills, CA: Sage.

Hirshi, T., & Gottfredson, M. (1983). Age and the explanation of crime. American Journal of Sociology, 89, 552-584.

Hoffman, P. B. (1983). Screening for risk: A revised Salient Factor Score (SFS 81). Journal of Criminal Justice, 11, 539-547.

Hoffman, P. B., & Adelberg, S. (1980). The Salient Factor Score: A non-technical overview. Federal Probation, 44, 44-52.

Hoffman, P. B., & Beck, J. L. (1974). Parole decision-making: A salient factor score. Journal of Criminal Justice, 2, 195-206.

Hoffman, P. B., & Beck, J. L. (1980). Revalidating the Salient Factor Score: A research note. Journal of Criminal Justice, 8, 185-188.

Hoffman, P. B., & Beck, J. L. (1984). Burnout -- age at release from prison and recidivism. Journal of Criminal Justice, 12, 617-623.

Inciardi, J. A., Babst, D. V., & Koval, M. (1973). Computing mean cost rating (MCR). Journal of Research in Crime & Delinquency, 10, 22-28.

Jackson, D. N. (1971). The dynamics of structured personality tests: 1971. Psychological Review, 78, 229-248.

Jenkins, D. (1984). Well-worn questions and worn-out answers. Criminal Justice, 2(1), 1-4.

Johnson, D. L., Simmons, J. G., & Gordon, B. C. (1983). Temporal consistency of the Megargee inmate typology. Criminal Justice & Behavior, 10, 263-268.

Kelley, C. (1976). Crime in the United States. Washington, D.C.: U.S. Government Printing Office.

Knight, R., Prentky, R., Schneider, B., & Rosenberg, R. (1983). Linear causal modeling of adaptation and criminal history in sexual offenders. In K. T. Van Dusen & S. A. Mednick (Eds.), Prospective studies of crime and delinquency (pp. 303-341). Boston: Kluwer-Nijhoff.

Ladouceur, P., & Temple, M. (1985). Substance abuse among rapists: A comparison with other serious felons. Crime & Delinquency, 31, 269-294.

Lee, E.T. (1980). _Statistical methods for survival data analysis_. Belmont, CA: Lifetime Learning Publications.

Lewis, D. O., Shanok, S. S., Grant, M., & Ritvo, E. (1983). Homicidally aggressive young children: Neuropsychiatric and experiential correlates. _American Journal of Psychiatry_, _140_, 148-153.

Loeber, R. (1982). The stability of antisocial and delinquent child behavior: A review. _Child Development_, _53_, 1431-1446.

Loeber, R., & Dishion, T. (1983). Early predictors of male delinquency: A review. _Psychological Bulletin_, _94_, 68-99.

Louscher, P. K., Hosford, R. E., & Moss, C. S. (1983). Predicting dangerous behavior in a penitentiary using the Megargee typology. _Criminal Justice & Behavior_, _10_, 269-284.

McCleary, R. (1978). _Dangerous men: The sociology of parole_. Beverly Hills, CA: Sage.

McCord, J. (1983). A longitudinal study of antisocial behavior. In K. T. Van Dusen & S. A. Mednick (Eds.), _Prospective studies of crime and delinquency_ (pp. 269-276). Boston: Kluwer-Nijhoff.

Magnussen, D., Stattin, H., & Duner, A. (1983). Aggression and criminality in a longitudinal perspective. In K. T. Van Dusen & S. A. Mednick (Eds.), _Prospective studies of crime and delinquency_ (pp. 277-301). Boston: Kluwer-Nijhoff.

Martin, R. L., & Guze, S. B. (1983). Risk factors and personality disorders. In D. A. Regier & G. Allen (Eds.), _Risk factor research in the major mental health disorders_ (pp. 95-110). Rockville, MD: U.S. Department of Health.

Mednick, S. A., Gabrielli, W. F., Jr., & Hutchings, B. (1983). Genetic influences in criminal behavior: Evidence from an adoption cohort. In K. T. Van Dusen & S. A. Mednick (Eds.), _Prospective studies of crime and delinquency_ (pp. 39-56). Boston: Kluwer-Nijoff.

Meehl, P. (1954). _Statistical v. clinical prediction: A theoretical analysis and a review of the evidence_. Minneapolis, MN: University of Minnesota Press.

Meehl, P., & Rosen, A. (1955). Antecedent probability and the efficacy of psychometric signs, patterns, or cutting scores. _Psychological Bulletin_, _52_, 194-216.

Megargee, E. I. (1977). The need for a new classification system. _Criminal Justice & Behavior_, _4_, 107-114.

Megargee, E. I. (1982). Psychological determinants and correlates of criminal violence. In M. E. Wolfgang & N. A. Weiner (Eds.), Criminal violence (pp. 81-170). Beverly Hills, CA: Sage.

Megargee, E. I., & Bohn, M. J., Jr. (1977). Empirically determined characteristics of the ten types. Criminal Justice and Behavior, 4, 149-210.

Megargee, E. I., & Dorhout, B. (1977). Revision and refinement of the classification rules. Criminal Justice and Behavior, 4, 125-148.

Meyer, J., Jr., & Megargee, E. I. (1977). Initial development of the system. Criminal Justice and Behavior, 4, 115-124.

Millard, P., & Brown, R. C. (1985). New NIC director gives his views. Corrections Today, 47(4), pp. 64-68, 70.

Moberg, D. O., & Ericson, R. C. (1972). A new recidivism outcome index. Federal Probation, 36(2), 50-57.

Monahan, J. (1978). The prediction of violent criminal behavior: A methodological critique and prospectus. In A. Blumstein, J. Cohen, & D. Nagin (Eds.), Deterrence and incapacitation: Estimating the effects of criminal sanctions on crime rates (pp. 244-269). Washington, D.C.: National Academy of Sciences.

Monahan, J. (1981). Predicting violent behavior: An assessment of clinical techniques. Beverly Hills, CA: Sage.

Monahan, J. (1984). The prediction of violent behavior: Toward a second generation of theory and policy. American Journal of Psychiatry, 141, 10-15.

Mosier, C. I. (1951). Problems and designs of cross-validation. Educational and Psychological Measurement, 11, 5-11.

Moss, C. S., Johnson, M. E., & Hosford, R. E. (1984). An assessment of the Megargee typology in lifelong criminal violence. Criminal Justice and Behavior, 11, 225-234.

Murphy, T. (1980). Michigan risk prediction: A replication study. Final Report. Lansing, MI: Department of Corrections, Bureau of Programs.

Murphy, T. H. (1985). The Iowa risk replication study: An evaluation of the Iowa risk assessment model on a sample of Michigan parolees. Lansing, MI: Department of Corrections, Program Bureau.

Norusis, M.J. (1983). SPSS:X introductory statistics guide. Chicago, Ill: SPSS Inc.

Nunnally, J. C. (1978). Psychometric theory (2nd ed.). New York: McGraw-Hill.

Peay, J. (1982). 'Dangerousness' -- ascription or description? In P. Feldman (Ed.), Developments in the study of criminal behaviour: Vol. 1 (pp. 201-227). New York: John Wiley.

Petersilia, J. (1985a). Rand's research: A closer look. Corrections Today, 47(3), pp. 37, 40.

Petersilia, J. (1985b). Rand's Research: Felony probation. Corrections Today, 47(3), pp. 36, 38.

Petersilia, J., Greenwood, P., & Lavin, M. (1977). Criminal careers of habitual felons. Santa Monica, CA: Rand.

Petersilia, J., & Honig, P. (1980). The prison experience of career criminals. Santa Monica, CA: RAND.

Phillpotts, G. J., & Lancucki (1979). Previous convictions, sentence and reconviction. London: Her Majesty's Stationery Office.

Press, S.J., & Wilson, S. (1978). Choosing between logistic regression and discriminant analysis. Journal of the American Statistical Association, 73, 699-705.

Pritchard, D. (1979). Stable predictors of recidivism: A summary. Criminology, 17, 15-21.

Rans, L. L. (1982). Murder release criterion study. Springfield, IL: Illinois Corrections Department.

Rans, L. L. (1984). The validity of models to predict violence in the community and prison settings. Lincoln, MA: Entropy.

Reed, G., & Amos, W. E. (1972). Improved parole decision-making. Federal Probation, 36(1), 16-18.

Regier, D. A., & Allen, G. (Eds.). (1983). Risk factor research in the major mental health disorders. (DHHS Publication No. (ADM) 83-1068). Rockville, MD: U.S. Department of Health.

Rice, M. E., Arnold, L. S., & Tate, D. L. (1983). Faking good and bad adjustment on the MMPI and Overcontrolled-Hostility in maximum security psychotic patients. Canadian Journal of Behavioural Science, 15, 43-51.

Robins, L. N. (1970). The adult development of the antisocial child. Seminars in Psychiatry, 2, 420-434.

Rotheram, M., & Marston, A. (1982). Aggressiveness as a stable individual characteristic in a criminal population. Corrective & Social Psychiatry &Journal of Behavior Technology, Methods, & Therapy, 28, 27-30.

Sanchez, J. E. (1984). An assessment of childhood and adulthood factors as predictors of violent criminality among a male population. Dissertation Abstracts International, 45, 2266A. (University Microfilms No. 84-23, 100).

SEARCH Group, Inc. (1976). Dictionary of criminal justice terminology. Washington, D.C.: U.S. Government Printing Office.

Sellin, T., & Wolfgang, M. (1964). Measurement of delinquency. New York: John Wiley & Sons.

Simon, F. (1971). Prediction methods in criminology. London: Her Majesty's Stationery Office.

Smith, A. B., & Berlin, L. (1979). Introduction to probation and parole (2nd ed.). St. Paul: West.

Solomon, L., & Baird, S. C. (1981). Classification: Past failures, future prediction. Corrections Today, 43(3), 4, 6, 34.

Speckart, G. (1985). Narcotics and crime: A multisample multimethod approach (Doctoral dissertation, University of California, Los Angeles, 1984). Dissertation Abstracts International, 45, 2998A.

Spellacy, F. (1978). Neuropsychological discrimination between violent and nonviolent men. Journal of Clinical Psychology, 34, 49-52.

SPSS, Inc. (1986). SPSS^x user's guide. New York: McGraw-Hill.

Stageberg, P. (1983). Risk assessment: An innovation whose time may have come. Iowa Review Quarterly, 2(1), 12-15.

State of Iowa. (1983a). The impact of objective parole criteria on parole release rates and public protection: An analysis of the application of the "Parole Guidelines System" to parole release decision-making. Final Report to the General Assembly of Iowa. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

State of Iowa. (1983b). Offender risk assessment: The Iowa model, Coding forms and procedures. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

State of Iowa. (1984a, August). A comparative study of the predictive validity of classification instruments. Paper presented at the 114th Congress of Corrections, American Correctional Association, San Antonio, TX.

State of Iowa. (1984b). Risk assessment in Iowa: An overview. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

State of Iowa. (1985a). Comparison of predictive validity: Alternative risk assessment models. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

State of Iowa. (1985b). Offender risk assessment: The Iowa model 1985 version coding specifications. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

State of Iowa. (1985c). Prison population, parole, and offender risk assessment in Iowa: An overview. Des Moines, IA: Office for Planning and Programming, Statistical Analysis Center.

State of Michigan. (1978). Summary of parolee risk study. Lansing, MI: Department of Corrections, Bureau of Programs.

State of Michigan. (1984). Prison crowding crisis imminent. Deadline, 17, pp. 1, 2.

Stone-Meierhoefer, B., & Hoffman, P. B. (1982). Presumptive parole dates: The federal approach. Federal Probation, 46(2), 41-57.

Tarasoff v. Regents of the University of California, 131 F. Supp. 14 (Cal., 1976).

Thompson, J. R. (1982). Symposium on the attorney general's task force on violent crime. Forward -- Remarks by governor James R. Thompson on the attorney general's task force on violent crime. Journal of Criminal Law & Criminology, 73, 867-874.

Thorndike, R. L., & Hagen, E. (1961). Measurement and evaluation in psychology and education (2nd ed.). New York: John Wiley & Sons.

Towberman, T. J. (1984). [Review of Careers of the violent: The dangerous offender project]. Corrections Today, 46(2), 142-145.

Travers, R. M. W. (1951). Rational hypotheses in the construction of tests. Educational and Psychological Measurement, 11, 128-137.

von Hirsch, A., & Gottfredson, D. M. (1983-84). Selective incapacitation: Some queries about research design and equity. New York University Review of Law & Social Change, 12(11), 11-51.

Wainer, H., & Morgan, A. M. B. (1982). Robust estimation of parole outcome. Journal of Research in Crime & Delinquency, 19, 84-107.

Warner, S. (1923). Factors determining parole from the Massachusett's Reformatory. Journal of Criminal Law and Criminology, 14, 172-207.

Wentz, C., & Oldroyd, R. J. (1979). Rational risk assessment for probationers (NCJ No. 64266). Washington, D.C.: National Criminal Justice Reference Service.

West, D. J. (1982). Delinquency: Its roots, careers and prospects. London: Heinemann.

Wilkins, L. T. (1980). Problems with existing prediction studies and future research needs. The Journal of Criminal Law & Criminology, 71, 98-101.

Williams, K. M. (1979). The scope and prediction of recidivism (PROMIS Research Project Pub. No. 10). Washington, D.C.: Institute for Law and Social Research.

Wolfgang, M. E. (1983). Delinquency in two birth cohorts. In K. T. Van Dusen & S. A. Mednick (eds.), Prospective studies of crime and delinquency (pp. 7-16). Boston: Kluwer-Nijhoff.

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

Zwanenburg, M. A. (1977). Prediction in criminology. Atlantic Highlands, NJ: Humanities Press.