University of Nevada, Reno

Picture Perfect: Predicting the Model Ex-Offender

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Arts in Criminal Justice

by

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Abstract

The cost of imprisonment remains high. Budgetary constraints faced by most states have resulted in an increased interest in reducing prison populations while simultaneously reducing recidivism rates. The latter goal has encouraged a renewed interest in offender reentry and reintegration. There are a multitude of reasons why offenders find themselves back in the criminal justice system; however, by identifying these issues, appropriate measures can be taken to reduce recidivism. This research uses data from Project Pride, a Nevada job readiness program, to examine the effect individual-level factors have on an offender's likelihood to successfully reintegrate. By using logistical regression, this analysis attempts to determine which factors are most likely to predict a person will remain in the community and out of prison. The ability to determine who will most and least likely succeed upon reentry can help guide effective correctional practices in Nevada.

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Chapter One

Introduction

Corrections and Criminal Justice Responses to Crime

Corrections is the branch of the criminal justice system in America that uses both government and private agencies to punish, supervise, and manage the accused and convicted (Schmalleger & Smykla, 2012). Some of these agencies and departments include probation, parole, jails, prison and other community correctional programming (Quinn, 2003). The goal and function of corrections is fluid because it is directed by the morality and political climate of a particular time period (Quinn, 2003). These underlying factors direct how the system should effectively operate in response to criminal behavior.

There have been five primary criminal justice responses to deviant behavior throughout history: restoration (Weitekamp, 1999), retribution, deterrence, incapacitation, and rehabilitation (Garland, 1990). Each of these responses has been used throughout history, based on the economic, cultural, and political principles of the time (Quinn, 2003). When a society changes how they view criminal behavior; such as believing that this behavior is learned rather than biologically driven, responses to crime will shift to coincide with these beliefs (Stohr & Walsh, 2012).

The first response, restoration, is the motivating philosophy when offenders are ordered to repair the damages done to the victim, the victim’s family, or the community (Weitekamp, 1999). This type of response is more likely to require informal practices such as restitution, where the offender pays the victim or victim’s family an agreed upon sum, to avoid a more formal sentence of supervision within a jail or prison facility (Quinn, 2003). Other acts of restoration include mediation between the offender and victim, and requiring the offender to complete community service hours (Weitekamp, 1999).

Retribution is one of the oldest forms of social control. This is best exemplified in the form of retaliation or vengeance (Garland, 1990). For example, if an offender injured the victim, the best way to right the wrong was to allow the victim to injure the offender in a similar fashion (Paternoster, Brame, & Bacon, 2008). The issue with utilizing retribution in today's society is that retaliation can cause more disruption and damage by creating a cycle of vengeance (Paternoster, Brame, & Bacon, 2008; Stohr & Walsh, 2012).

Deterrence can be directed at two different populations; specific deterrence is used to stop current criminals from committing further crime, whereas general deterrence attempts to dissuade non-criminals to avoid committing crimes in the future (Andenaes, 1975; Garland, 1990). Deterrence is best used when punishment is certain, swift, and severe (Bentham, 1879; marchese di Beccaria, 1819). This means that a punishment must always follow the crime, it must happen quickly, and be harsh enough to cause the would-be offender to choose not to commit the crime (Bentham, 1879; marchese di Beccaria, 1819).

Incapacitation involves the physical removal of the offender from society, through the incarceration process, so that they will be unable to commit further crimes against society (Garland, 1990; Zimring, 2007). Today, it is the most common form of punishment given to serious offenders (Mitford, 1976; Zimring, 2007).

Finally, rehabilitation attempts to treat the offender by addressing the underlying problems that led to the criminal behavior (Garland, 1990). This response is controversial because rehabilitation attempts to help the offender rather than just offering a punitive response (Stohr & Walsh, 2012). Rehabilitation focuses on reducing the causal factors that enhance the offender's likelihood to commit crime (Garland, 1990).

These different responses are both conflicting and cyclical (Tonry, 2004), and their popularity and use is reflective of the current social and cultural values (Stohr & Walsh, 2012; Sumner, 1996). The use of prisons historically in America was to help rehabilitate an offender through solitude and penitence (Quinn, 2003). When this notion started to lose popularity, it gave way to retribution and deterrence and the use of prisons as warehouses (Quinn, 2003). This swinging of the pendulum can still be seen today.

Contemporary American Corrections

"Nothing works" and the current use of corrections.

During the 1970's, rehabilitation was nearing the end as the crime rate was rising and a new study, the "Martinson Report", was released which detailed the ineffective nature of rehabilitation (Martinson, 1976; Pratt, 2009). In the 1980s, political pressures to "get tough" on crime were combined with the ongoing War on Drugs, resulting in harsh penalties for non-violent drug offenders (Zimring, 2007). Treatment programs were ended, prison populations increased, and society returned to incapacitation as a response to crime (Alexander, 2012; Quinn, 2003). The soaring cost of warehousing vast prison populations encouraged states to reconsider the goals of the past, and the popularity of rehabilitation programs began to increase.

Issues created in prisons.

Prisons are considered total institutions (Goffman, 1961). A total intuition is "…a place of residence and work where a large number of like-situated individuals, cut off from the wider society for an appreciable period of time, together lead an enclosed, formally administered round of life…" (Goffman, 1961, p. 6). The nature of the total institution often creates a prison subculture and "prisonization" where convicts and correctional officers learn to take on new roles they have developed due to the nature of the total institution (Clemmer, 1940). This prisonization happens for two primary reasons. First, the inmate is cut off from the former role he or she played in society and they must now accept the role of inmate, a process known as mortification (Clemmer, 1940). Second, the inmate may bring their criminal roles they held in society into the prison, this is known as importation theory (Carroll, 1974; Irwin & Cressey, 1962).

Both of these theories lead to a prison subculture where a convict will suffer, as Gresham Sykes (2007) describes, the pains of imprisonment. These pains include the loss of security, autonomy, heterosexual relationships, liberty, and goods and services (Sykes, 2007). In prison, a convict has no independence, they have no freedom, no means of security, they are unable to maintain physical heterosexual relationships, and the only goods and services provided can be purchased through their commissary (Stohr & Walsh, 2012; Sykes, 2007). These pains of imprisonment often lead a convict to desire what security and goods and services can be provided by means of joining a gang (Stohr & Walsh, 2012). Gangs can provide security, but may also encourage violent behavior that ultimately endangers others in prison (Pratt, 2009). This is why effective prison and reentry programming should be utilized to reduce anti-social behavior before a person returns to society.

Challenges to Reentry

There are many barriers to rehabilitating offenders who are imprisoned. The prison subculture is very prominent in closed institutions like medium and maximum-security level prisons (Clemmer, 1940). The subculture promotes violent and aggressive behaviors that are contrary to the norms of society (Fagin, 2013). This maladaptive behavior learned by prisoners, if transferred to the outside upon release, will only increase their chances of reoffending (Fagin, 2013).

Not only are the offenders not able to be rehabilitated, but their families and communities are negatively impacted by incarceration as well (Alexander, 2012; Pratt, 2009). When a family member, such as a father who is the sole provider for the family, is placed in prison, the family must now attempt to replace that source of income (Pratt, 2009). This strains the family and leaves many children in single-parent homes (Alexander, 2012). These collateral consequences can be devastating.

Effective offender release from incarceration has become one of the greatest challenges in the criminal justice system. Due to the heavy reliance on incapacitation through incarceration as crime control (Pratt, 2009), offenders suffer while in prison, and then at the completion of their sentence they are released back to society without any treatment or programming. Crime rates and social safety is too often compromised by the release of these prisoners (Pratt, 2009). Offenders who are released at the completion of their respective sentences also go back into society without any supervision requirements. They may lack the proper tools to succeed, and they also lack the support (in the form of a parole officer) to connect with jobs and other necessary supports (Fagin, 2013). These offenders had no programming while in prison; they may lack educational credentials, and viable work skills. Their attempts to find employment once in society are often futile because of the ex-convict or ex-felon label now placed upon them (Alexander, 2012). Given all these limitations and obstacles, society is still surprised when these offenders reoffend following release. Prison reentry programs attempt to identify the factors associated with successful reentry, and provide programming within the prison prior to release to build those skills necessary for survival upon release.

Chapter Two

Literature Review

Factors Associated with Successful and Unsuccessful Reentry

Reentry and individual factors.

Many of the offenders in prison today are serving determinate sentences because of the "just desserts" model of sentencing, which became popular in the late 1980's (Zimring, 2007). Offenders sentenced under these guidelines received longer sentences relative to similar offenders in the past, and many were not allowed sentence reductions for good time or program participation. This resulted in numerous offenders being released unconditionally at the end of their sentence, and without supervision or any help with their transition from prison to the community (Seiter & Kadela, 2003). Because of the lack of reentry assistance, many ex-offenders ultimately found themselves back in the system through the commission of new crimes (Seiter & Kadela, 2003). Some data disturbingly suggested that up to one third of those released on parole would be rearrested within six months (James, 2014; Petersilia, 2003). The question remains, what factors will influence the likelihood someone will reoffend once released from prison? Successful reentry is not only dependent on providing the offender with adequate programming and supervision, but other factors, such as: age, race, gender, gang affiliation, criminal history, education level, family and social ties, type of offense committed, and risk assessment scores may also greatly affect the reentry process for an offender and thereby the likelihood of re-offense. So important are these factors that many of them are used by police, prosecutors, judges, parole and probation, and parole boards to determine how the offender progresses through the justice system. (Huebner &

Bynum, 2008). This portion of the review will first discuss what constitutes re-offense and the issues surrounding the term recidivism. Following this, the literature on the aforementioned factors will be discussed in the context of release from jail and prison and whether these factors help or hinder a persons' release. Finally, Sampson and Laub's (2003) life-course theory will briefly be discussed in regards to the factors that may encourage a person to desist from deviant behavior.

Recidivism as a measure of success.

Much of the research within the field of criminal justice relies on recidivism as the primary metric to identify the successes and failures of the justice system. The primary issue with using recidivism as a dependent variable concerns the varying definitions of what constitutes recidivism. Some definitions include parole violations, parole revocations (when a person has violated the terms of their parole and therefore may be rearrested or reconvicted), rearrest for a new offense similar to the original offense, rearrest for any offense, reconviction, or re-incarceration (Maltz, 1984). The inability to settle on a single universal definition of failure means that recidivism rates can easily be manipulated to over-or-understate the scope of the problem, and conclusions drawn from some research projects may be incompatible with other conclusions. Furthermore, measures of recidivism typically do not include measures of "success" or how well an ex-offender is doing while in the community. The lack of a qualitative measurement of success may imply that many crimes go unreported and therefore the term recidivism should be taken with caution, as there may be many offenders who reoffend without being discovered, and therefore are never considered recidivists (Maltz, 1984). Additionally, tracking recidivism properly requires following the same offender over a period of time to ensure the data also reflects when the offender has recidivated. This is a challenge, as researchers can easily lose track of offenders, which will consequently understate the recidivism rate. Regardless of the faults, recidivism remains the most common metric used to determine offender success and failure in the criminal justice system.

An examination of the variables used to predict recidivism.

Race.

Race is one of the most common demographic variables used to determine an offender's risk of reoffending. Some studies show that minorities are in general more likely to reoffend once released (Clarke, Yuan-Huei, & Wallace, 1988; Irish, 1989; Piquero, Jennings, Diamond, & Reingle, 2015). More specifically, research shows African Americans are more likely to reoffend than both Caucasians and Hispanics (Langan & Levin, 2002; McGovern, Demuth, & Jacoby, 2009; Piquero et al., 2015; Steen & Opsal, 2007). African Americans are also more likely than Caucasians to violate their parole (Steen & Opsal, 2007), be rearrested, reconvicted, and re-incarcerated for a new offense (Langan & Levin, 2002; McGovern et al., 2009). Durose, Cooper, and Snyder (2014) found in a study of over 280,000 offenders released from prison in 30 different states between 2005 and 2010 that Caucasians and Hispanics were less likely to be rearrested when compared to African Americans. Other studies suggest that Hispanics are less likely to be rearrested and reconvicted than African Americans and Caucasians (McGovern, Demuth, & Jacoby, 2009). However, Hughes, Wilson, & Beck (2001), when considering persons on parole in the United States between 1990 and 2000, found that Caucasians were more likely to reoffend than both Hispanics and African Americans.

Horowitz (1983) theorized that this finding may be due to the Hispanic honor-based culture, which may reduce the likelihood a person will reoffend because the label attached to being a criminal is highly stigmatized. Ultimately, the preponderance of research seems to suggest that, in general, African Americans are most likely to reoffend, but the reoffense patterns for Caucasians and Hispanics are still uncertain.

Gender.

Historically, males have made up the largest proportion of the prison population in America, but they are no longer the fastest growing population (Carson & Golinelli, 2013). Langan and Levin (2002) found that females were less likely to be rearrested and reconvicted than males. In support of this finding, a later study by Durose et al. (2014) found males were 10% more likely to be rearrested following release from prison than females. Females are more likely to reoffend if they have had prior arrests and if they are released unconditionally rather than on some form of parole (Langan & Levin, 2002; Solomon, Kachnowski, & Bhati, 2005). However, in a study of those released from jail in Texas, McCoy and Miller (2013) found that males and females actually exhibited similar non-violent reoffense patterns. It seems that males make up the majority of reoffenses, however, with the growing number of females entering the justice system, their reoffense patterns may become similar over time. Although female crime commission is still lower than male crime commission, females are the fastest growing prison population today (Carson & Golinelli, 2013) and therefore in the future may exhibit higher recidivism rates because of this (Adler, 1975; Chesney-Lind & Pasko, 2012).

Education level.

In a sample of over 20,000 probationers from North Carolina, Clarke et al. (1988) found that those with lower levels of education were most likely to be rearrested within three years. Conversely, Bahr, Harris, Fisher, and Armstrong (2010) discovered that education level was not a significant factor in determining whether someone would be successfully discharged from parole after three years. Wikoff, Linhorst, and Morani (2012) noticed that those who had a high school diploma or equivalent degree were less likely to be reconvicted once released, compared to those who had not received their degree. Further evidence suggests that those who participate in correctional educational programming while in prison are less likely to be rearrested, reconvicted, and reincarcerated than those who do not participate (Lockwood, Nally, Ho, & Knutson, 2012; Stevens & Ward, 1997). In two studies of Florida juveniles, Blomberg, Bales, Mann, Piquero, and Berk (2011) and Blomberg, Bales, and Piquero (2012) found that those who were released from juvenile institutions with higher levels of educational attainment were more likely to return to school and stay in school than those with lower levels; they were also less likely to be rearrested or to commit further serious offenses than the comparison group. Research seems to suggest that higher levels of educational attainment are related to successful reentry.

Gang affiliation.

Gangs can encourage deviant behavior in both adolescents and adults. Research has consistently shown that both female and male juveniles who are gang affiliated are more likely to be rearrested, reconvicted, and reincarcerated when released from a juvenile institution (Archwamety & Katsiyannis, 1998; Benda & Tollett, 1999; Caudill, 2010; Toller & Benda, 1999; Trulson, Marquart, Mullings, & Caeti, 2005). Benda, Corwyn, and Toombs (2001) found that youths who were gang affiliated were more likely to enter into the adult correctional system after being released from a juvenile detention center than those who were not gang affiliated. Even for adults, rearrests and reconvictions are more likely for those who are gang affiliated than those who are not (Dooley, Seals, & Skarbek, 2014; Huebner, Varano, & Bynum, 2007). Clearly, the research shows that those who are gang affiliated tend to recidivate more often than those who are not affiliated.

Criminal history.

Past criminal behavior has also historically been used to predict whether a person will reoffend in the future, which is why it is often used as a primary classification factor on risk assessment instruments (Gendreau, Little, & Goggin, 1996). It is also used throughout the criminal justice process as a factor in deciding whether an officer should make an arrest, to whether a parole board should release an offender (Blumstein, Farrington, & Moitra, 1985; Bushway & Piehl, 2007; Gottfredson & Gottfredson, 1985; Maxfield, 2005). Similar to the aforementioned findings on juveniles and gang affiliation, juveniles who have a prior criminal record are more likely to recidivate than those without such a criminal history (Blumstein et al., 1985; Cottle, Lee, & Heilbrun, 2001). Studies have shown that those released from prison are more likely to be rearrested, reconvicted, and more likely to have a parole revocation if they have a prior criminal record (Durose et al., 2014; Langan & Levin, 2002; Maxfield, 2005). Furthermore, the more prior arrests a person has, the more likely they are to recidivate. Langan and Levin (2002) also found that those who served time in prison are more likely to be rearrested than those who have not served a prison sentence. It seems that past criminal history is a valid predictor of whether someone will reoffend in the future.

Prisonization or prisons as criminogenic institutions.

Prisonization, the socialization of offenders to prison culture (Clemmer, 1940), is revisited in this section because it is still undecided as to whether prisons are criminogenic, therapeutic, or deterrent. Prisons are considered total institutions because correctional officers and prisoners are separated from society and must take on unique and rigid rolls (Austin & Irwin, 2001). The degree to which offenders take on these rolls is dependent on the type of prison, but when prisoners abide by the inmate code of conduct it can encourage further negative behaviors (Sykes, 2007). This is a challenging factor to test and very few studies have looked at the effect of prisonization on recidivism. Sampson and Laub (1993) conducted a study on both incarcerated juveniles and adults to determine if recidivism was due to previous imprisonment. They found that prisons are not directly criminogenic, but may affect recidivism indirectly by hindering the ability of the person to maintain a job once released (Sampson & Laub, 1993). In a meta-analysis of prisonization studies, Gendreau, Cullen, and Goggin (1999) found that prisons are less likely to deter criminals from future offending, and instead increase recidivism. Spohn and Holleran (2002) focused on felons on parole in Missouri and found that those who had been imprisoned prior to parole were more likely to recidivate. A more recent meta-analysis conducted by Villettaz, Killias, & Zoder (2006) on those sentenced to prisons versus alternative sanctions found little evidence that sentences to prison contributed to any rise or decrease in crime. Similarly, Nagin, Cullen, and Jonson (2009) examined existing literature on custodial compared to non-custodial settings and also determined that prisons had little to no impact on recidivism. More specifically, Vieratis, Kovandzic, & Marvell (2007) and Bales and Piquero (2012) found that prisoners were more likely to reoffend if they had served prison sentences compared to those who had not. Although this concept is challenging to test, it is possible that prisons may encourage deviant behavior more than if a person was placed in an alternative to prison.

Risk assessments.

Risk assessments are used by correctional agencies to determine the risk a person poses to society, in order to determine what specific needs are unmet (Bonta, 1996). There are many different types of risk assessment tools that have been developed over the years. Most tools consider an offender's criminal history, family and or marital status, finances, education level, employment, leisure or recreational peers and companions, substance abuse, attitudes, and emotions (Bonta, 1996). Lower scores indicate the individual poses a low risk to society and has fewer unmet needs. (Bonta, 1996). The most predictive tools are those that measure both static and dynamic risk, which are those that will not change (static) and those that can change (dynamic) if proper needs are met (Bonta, 2002). Nevada uses a modified version of the Wisconsin Risk Needs Assessment. Henderson (2007) and Henderson and Miller (2013) have tested the accuracy and reliability of the Wisconsin Risk Needs Assessment on Texas probationers. The studies looked at the application of the instrument in its original form (Henderson, 2007) and then again with modifications (Henderson & Miller, 2013). In both instances, the instrument failed to accurately assess the true risk and needs of an offender (Henderson, 2007; Henderson & Miller, 2013).

Type of offense.

Some studies suggest that the type of criminal offense committed may affect a persons' rate of reoffense. Langan and Levin (2002) found burglars, larcenists, and those convicted of possession of stolen property were most likely to be rearrested, while those with the lowest recidivism rates were offenders caught for driving under the influence (DUI) or a violent crime. However, Spohn & Holleran (2002) found that those convicted of either a drug possession or possession with the intent to sell, were more likely to be reconvicted than those who were originally convicted for either burglary or larceny. Solomon, Kachnowski, and Bhati (2005) found that property offenders were less likely to be arrested once on parole than those who had committed violent or drug-related crimes. Similar to Langan and Levin (2002) and Spohn and Holleran's (2002) findings, recent research suggests those who were originally convicted of burglary, larceny, forgery, or drug offenses are more likely to be rearrested than those who committed a violent crime or public order offense (Durose et al., 2013).

Life-Course Theory

Life-course theory is an integrated theory that falls under the category of general developmental criminology. Life-course theory focuses on the factors and experiences that attempt to predict whether or not a person will commit crimes over the entirety of his or her life (Laub & Sampson, 2003). This theory suggests that certain childhood experiences will make it more likely for a person to become antisocial and deviant in later life (Laub & Sampson, 2003). This theory claims that there are other factors and events that serve as protective factors and may help a person desist from crime (Laub & Sampson, 2003). These include but are not limited to: marriage, employment, military service, and becoming a parent (Laub & Sampson, 2003). Some of these events are more likely to happen at certain ages. Laub and Sampson (2003) have found that in their longitudinal studies, age is a major factor in crime desistance. As people age, they commit less and less crime (Laub & Sampson, 2003). Specifically, crime commission peaks during adolescence and early adulthood and then begins to drop-off, especially after age 40 (Ulmer & Steffensmeier, 2014).

Chapter Three

Research Questions

The previous literature can be useful in determining which factors affect the likelihood that an offender in Nevada will be released and will not return to the justice system. Prior literature suggests that the model ex-offender would be an older white female that has at least a high school degree. She would not be gang affiliated, or have served a prior prison sentence or have any prior criminal record, and was convicted of a DUI related offense rather than a property or drug crime. This thesis intends to explore and test this prediction on data drawn from various justice agencies in the state of Nevada, and determine if these same variables contribute to successful reentry in Nevada. Although the previous literature focused on recidivism as the dependent variable, for simplicity in this study, the outcome variable will be whether a person is in a facility or out of a facility.

First, is it possible to create a model that will predict which factors are more likely to influence a person's desistance from crime? Second, do a combination of these previous variables influence whether or not a person will reintegrate successfully? Third, which variables are more likely to influence a successful reentry, and which variables are least likely to be associated with successful reentry?

Chapter Four

Methods

Data Collection

The data obtained for this thesis came from three sources: the Nevada Department of Corrections (NDOC), the Nevada Department of Public Safety, Office of Parole and Probation, and the NDOC website. The NDOC originally provided data from a sample of prisoners who had completed Project Pride between the years 2011 and 2013. Project Pride is a prison reentry program located in southern Nevada at Casa Grande Correctional Facility. Six hundred and forty nine cases were originally provided, however, due to missing key variables, 403 cases were used in the final analyses. For an entire listing of the variables provided by the NDOC, Parole and Probation, and the NDOC website please see Table 1.

In order to combine the above variables into one dataset, the exclusion criteria included: participants who had no current offense listed in the current offense category on the original NDOC demographics file. This was decided because current offense was going to be used as a predictor variable. Other cases were excluded if they were found on the Parole and Probation files, but not on the NDOC file, which resulted in these offenders lacking key demographic and current offense variables. Others offenders were excluded if their NDOC website demographic information did not match the demographic information provided by the NDOC or Parole and Probation.

Many of the NDOC variables contained cells that were coded as yes or no because they were used as a checklist for Project Pride. These variables, found in Table 2, were not used in the analyses because all those who participated had to have these items by the end of Project Pride, so there was little variation between participants as to whether they had a yes in the categories.

Cleaning and Combining Data

The first step was to combine the different files into one data set that would eventually be placed into the data analysis program (IBM's Statistical Package for the Social Sciences (SPSS) version 22). In order to combine the NDOC and Parole and Probation variables, the different identification numbers used by each agency had to be matched. NDOC relies on inmate number and their NDOC ID number (as found on the NDOC website) to identify inmates, whereas Parole and Probation uses what is called an OTIS or PP Bin Number to identify parolees. NDOC provided an excel file with the inmate ID number, inmate name, gender, age, and OTIS Bin. By referring to these data, an inmate could be identified by both their NDOC and Parole and Probation numbers, allowing these two data sets to be accurately merged into a single data file. The violations and discharge sheets included case numbers that linked to violations, discharges, and dates reported for each so that new variables could be created that corresponded to a result or a discharge in response to a parole violation. This also allowed for the most recent violation or discharge to be added as a new variable into the data set. The new violation variables included: recent violation, second recent violation, third recent violation, fourth recent violation, and fifth recent violation, and total number of violations. New discharge variables included: recent result/charge, second result/charge, third result/charge, fourth result/charge, fifth result/charge, and total number of discharges. Both violation and discharge categories only include up to the fifth violation and fifth result/charge because the greatest number of violations and discharges recorded was five for an inmate. Those who were not on the Parole and Probation files were coded as system missing in all categories except for total number of violations and total number of discharges. The total number variables coded those without a violation or discharge as zero for having no violations or discharges.

For those offenders with multiple risk assessment scores, a new variable was created to reflect the number of risk assessments the offender had received. Risk assessment score variables included: lowest social score, highest social score, lowest offense score, highest offense score, lowest total score, highest total score, most recent score, and number of scores. These categories were created to ensure if an inmate was coded with multiple scores, their change in risk and/or needs could be considered in the analyses. Since scores were not dated but were accompanied by case numbers, these case numbers could be checked back with violation and discharge cases to determine which case number was the most recent; if a case number was not associated with a set of scores, it was coded as system missing in the final dataset.

Other variables were created throughout the process, which included: second recent offense, third recent offense, and number of offenses. In the original current offense category supplied by the NDOC, multiple offenses were indicated by an offense listed in a cell then a forward slash, then another offense listed. Each offense following a forward slash was coded into a separate cell where it received a unique variable name to differentiate it from the original offense. A maximum of three current offenses were recorded for each inmate.

The current offense category originally included a multitude of various offenses (please see Table 3 for a complete listing of the offenses). A variable was created to combine similar offenses into more general categories in order to decrease the noise created by the coding process. This new current offense category recoded offenses into: BRG, all burglary related offenses, CS, all controlled substance related offenses, DUI, all DUI related offenses, FPF, all felon in possession of firearm related offenses, FRG, forgery related offenses, GL, larceny or Grand Larceny related offenses, PSP, all possession of stolen property related offenses, TFT, all theft related offenses, and OTHER, for those offenses that did not fit the previous categories. Each category was then transformed into a dichotomous variable; the new coding is shown in Table 4.

Coding Data

Dependent variables.

Finally, two possible dependent variables were created using the current custody level and current institution information found on the NDOC website. First, the level of release variable was created. For each inmate, the possible categories for current institution included: inactive, parole, camp, prison, or residential confinement. For each inmate the possible categories for current custody level included: unassigned, trustee, camp, or prison. Those in a current institution of prison could be in a custody level of either camp, minimum, medium, close, or max. Those who were in residential confinement were assigned to the category of trustee, and offenders who were on parole were unassigned in custody level. Finally, those who were no longer in the NDOC system were coded as inactive discharged for both custody level and current institution. Combining these two variables allowed for the creation of a new variable. This categorical variable became labeled 1-8, 1 being those in a maximum prison facility and 8 being those no longer in the system. These categories are also represented in Table 5.

Following this, an additional dichotomous dependent variable was created. This variable (In/Out) represented the offender's current placement either in some sort of facility or out of a facility. Those who were coded as one through six on level of release were recoded into "In a facility", while those who were coded as either a seven or eight were recoded into "Out of a facility".

Independent variables.

Other categorical variables were recoded into dichotomous variables to make analyses easier to interpret; the remainder of the variables and their re-coding are displayed in Table 6. The variables with unknown or missing information were recoded as system missing. However, because of the type of analyses, which will be discussed later on, and the amount of missing information in many of the original and created variables, only variables listed in Table 7 were considered for analyses.

Once the final dataset was compiled with the addition of the new variables into an SPSS file, the identifying characteristics of the participants were deleted to ensure anonymity.

Chapter Five

Analyses

All analyses were performed in IBM's Statistical Package for the Social Sciences (SPSS) version 22. Binary logistic regression was used as the multivariate analysis for this data set as a result of the research questions focus on predicting what types of factors affect successful release. This analysis is appropriate due to the dependent variable of in/out as dichotomous and logistic regression predicts the likelihood that certain independent variables will affect the percentage of cases falling into the "out" category.

Univariate Analyses

Before performing a logistic regression, a correlation matrix between the independent variables and the dependent variables of level of release and in/out was performed to determine if any significant correlations could be found. Level of release was used in the correlation matrix because it is acting as an ordinal level variable rather than dichotomous. A point biserial correlation (which is performed as a Pearson's correlation in SPSS) was used as the test of significance on the grounds that the in/out dependent variable was less than that of interval level data.

Multivariate Analyses

All logistic regression analyses were done with the independent variables entered simultaneously into the model. The first analysis focused on the independent variables that were found to be significant at the .05 level or higher in the correlation matrix. The second analysis was conducted on the variables only supplied by NDOC. The third analysis used the independent variables supplied by Parole and Probation. Finally, multiple combinations of the above variables were entered into the model to attempt to find the most predictive combination of factors.

Chapter Six

Results

Demographics

Before providing the findings of the analyses, it is important to understand the demographics of this sample of offenders. The mean age of the 403 offenders was 38.4 years old; the youngest person being 20 and the oldest being 72 years old (Table 8). Roughly 80% of the sample, or three hundred and twenty five of the 403 offenders were male (Table 9). Over half of the offenders were Caucasian, followed by African Americans as the next largest group (Table 10). Of the 101 offenders that provided information regarding marital status, 84 claimed they were not married (Table 11). The majority of offenders, 248 out of 397, had at least one dependent child (Table 12). Roughly seventy percent of the 389 offenders had at least a high school diploma (Table 13). Around 80% or 316 out of the 391 offenders were not gang affiliated (Table 14). Two hundred and eighty-nine offenders had a prior felony before coming to Project Pride (Table 15). Of the total sample, 54.6% of the offenders were not under any form of control in the Nevada criminal justice system, the next largest group was on parole, followed by those in a medium level security prison (Table 16). Three hundred and four or 75.4% of the sample were not in a facility. Almost one quarter of offenders had committed a burglary related offense and 18.9% of offenders had committed a controlled substance related offense (Table 17).

Univariate Analysis

Prior to running the logistic regressions, a correlation matrix of all variables used in the regression was created. Variables included in this matrix are presented in Table 18.

The variables that most significantly correlated with the dependent variable, in/out, were highest social risk assessment score and whether a person was charged with a DUI related offense. Highest social score was negatively correlated with in/out indicating that a person with a lower social risk assessment score would be more likely to be out of a facility. DUI was positively correlated with in/out indicating that a person out of a facility would be more likely to not be charged with a DUI related offense. These findings are shown in Table 19 with their respective levels of significance.

Multivariate Analyses

Binary logistic regression with variables that had significant correlations.

The first analysis used the following independent variables in the model: lowest offense score, highest social score, highest total score, number of NDOC IDs, number of total scores, number of parole hearings, controlled substance (dichotomous), DUI (dichotomous), and forgery (dichotomous). This included 364 of the 403 possible cases in the analysis. The classification table that does not include the effects of the independent variables will be referred to as the null model for the remainder of the thesis. This null model represents what chance a person has of either being in a facility or out of a facility. Due to the non-parametric nature of the dataset, by chance the null model correctly predicted which category a participant would be placed into 76.1% of the time, rather than 50% of the time (Table 20). The significance of the independent variables prior to inclusion in the model is shown in Table 21. The overall statistics were significant at the .01 level, while controlled substance and number of parole hearings were the only non-significant variables. After the variables were placed simultaneously into the model, the predictive power of the model did not change (Table 22). DUI was the only variable that remained significant once entered into the model, which is shown in Table 23.

Binary logistic regression with NDOC variables.

This analysis utilized the following NDOC variables: prior felonies, gender, gang affiliation, dependent children, race white non-white, married, age, number of offenses, high school degree, DUI, controlled substance, burglary, felon in possession of firearm, forgery, larceny, other offense, possession of stolen property, number of parole hearings, and number of NDOC IDs. This included 98 of the 403 possible cases in the analysis. The null model correctly predicted which category a participant would be placed into 66.3% of the time (Table 24). The significance of the independent variables when not included in the model is shown in Table 25; only DUI was significant at the .01 level. After the variables were placed simultaneously into the model, the predictive power of the model increased to 78.6% (Table 26). Table 27 shows that none of the variables were individually significant once entered into the model.

Binary logistic regression with Parole and Probation variables.

The Parole and Probation variables analysis included the following variables: lowest risk assessment offense score, highest risk assessment offense score, lowest risk assessment social score, highest risk assessment social score, lowest risk assessment total score, highest risk assessment total score, recent risk assessment total score, total number of scores, total number of violations, and total number of charges. One hundred and forty-eight of the 403 possible cases were included in the analysis. The null model correctly predicted which category a participant would be placed into 79.1% of the time (Table 28). None of the variables were significant before being placed into the model, which is shown in Table 29. After the variables were placed simultaneously into the model, the predictive power increased to 80.4% (Table 30). Table 31 shows that none of the variables were individually significant once entered into the model.

Binary logistic regression with different combinations of variables.

Combination one.

The first combination of variables included: lowest offense score, number of NDOC IDs, number of offenses, number of parole hearings, prior felonies, gender, age, dependent children, gang affiliation, race white non-white, married, and high school degree. This analysis included 98 of the 403 possible cases. The null model (Table 32) correctly predicted which category a participant would be placed into 66.3% of the time. Table 33 shows that no variables were significant prior to entering the model. After the variables were placed simultaneously into the model, the predictive power increased to 67.3% (Table 34). Still none of the variables were individually significant once placed into the model. Table 35 shows the variables once entered into the model.

Combination two.

The next combination of variables included all the variables from Combination One with the addition of the DUI variable. This included 98 of the 403 possible cases in the analysis. The null model (Table 36) correctly predicted which category a participant would be placed into 66.3% of the time. DUI was the only variable significant at the .01 level prior to being placed into the model, which is shown in Table 37. After the variables were entered into the regression equation, the predictive power of the model increased to 73.5% (Table 38). Table 39 shows that DUI was still significant at the .01 level once entered into the model.

Combination three.

The third combination of variables included: lowest offense score, number of NDOC IDs, number of offenses, number of parole hearings, prior felonies, gender, age, dependent children, gang affiliation, total number of violations, total number of discharges, race white non-white, married, high school degree, highest social score, highest total score, and number of total scores. This included 91 of the 403 possible cases in the analysis. The null model (Table 40) correctly predicted which category a participant would be placed into 68.1% of the time. Table 41 shows that highest social score and highest total score were the only significant variables before being placed into the model. After the variables were placed into the model, the predictive power increased to 76.9% (Table 42). Dependent children became significant once entered into the model as shown in Table 43.

Combination four.

The fourth combination of variables included: number of NDOC IDs, gender, dependent children, gang affiliation, married, number of offenses, number of parole hearings, prior felonies, race white non-white, highest social score, and number of total scores. This incorporated 92 of the 403 possible cases in the analysis. The null model (Table 44) correctly predicted which category a participant would be placed into 67.4% of the time. Highest social score was the only significant variable before being placed into the model, which is shown in Table 45. After the variables were placed simultaneously into the model, the predictive power of the model increased to 77.2% (Table 46). None of the variables were individually significant once entered into the model. Table 47 shows the variables once entered into the model.

Chapter Seven

Discussion

Multivariate Model: Significant Variables

The first analysis used lowest offense score, highest social score, dependent children, highest total score, number of total scores, controlled substance, DUI, and forgery to try and predict which cases would fall in a facility or out of a facility. Once placed into the model the logistic coefficient showed that a person who is more likely to be out of a facility will have a higher offense score, while having a lower social and total score, along with greater sets of scores overall. They are also more likely to be charged with a controlled substance or forgery related offense, rather than a DUI related offense. Although the majority of the variables in the logistic regression were significant, they exhibited the same overall predictive power as the null model. When looking at the classification tables for the null (Table 20) and the regression model (Table 22), it seems that the variables were least predictive in regards to those who would have been in a facility; it was only able to correctly predict this 6.7% of the time. However, it was able to correctly predict almost 98% of the time who would be either on parole or out of the system completely. This set of variables do not accurately predict success or failure since those who are in a facility are just as likely to have the same types of risk assessment scores and are only slightly more likely to be charged with a DUI related offense than those who are out of a facility.

Multivariate Model: NDOC Variables

The NDOC model had the most predictive power out of all the models, even though none of the variables were individually significant. This model found that those most likely to be on parole or out of the system would be white males with less education, who were younger, married, and had dependent children. They were more likely to have fewer NDOC IDs and parole hearings, to not be in a gang, to have more current offenses, and be charged with anything but a DUI related offense. This model was slightly less predictive of who would be out of a facility than the previous model; however, it was better at predicting who would be in a facility which is why it was much more predictive overall (Table 27). These findings suggest that demographics are better predictors of success and failure since this model was able distinguish more characteristics related to those who are in a facility in contrast to those who are not in a facility.

Multivariate Model: Parole and Probation Variables

The parole and probation model exhibited variables with the least amount of significance and highest coefficients, exponent of coefficients, and standard error. This uncharacteristic model, however, can be explained by the degree of multicollinearity among the predictor variables. Multicollinearity exists when there is a high rate of correlation among many of the predictor variables. In regards to the correlation matrix, the Parole and Probation predictor variables were significantly correlated with each other at the .01 level (see Table 48). When running a linear regression with level of release as the outcome variable, select parole and probation variables were shown to be collinear or multicollinear. The collinearity statistics showed that highest offense score and highest total score were collinear. This suggests that a high offense score, rather than a high social score, constitutes a significant portion of the overall total risk assessment score. Recent total score exhibited multicollinearity with lowest offense, lowest social, and lowest total score. Furthermore, recent total score was also multicollinear with highest offense, highest social, and highest total score. This is due in part to many participants only having one set of scores which would mean the recent score matched the total score and encompassed a significant portion of the lowest or highest offense and social scores. While this model can accurately predict who would be out of a facility every time (Table 30), these results should be taken with caution as it is a reflection of many of the independent variables predicting each other rather than success or failure of the offender upon release.

Multivariate Model: Combination One

The first combination focused on the NDOC variables without the inclusion of the offenses variables because the model was predicting those who would be out of a facility to have been charged with anything except for a DUI related offense. In comparison to the NDOC model, the predictive power of Combination One only increased by about 1%. While the model was able to predict 90% of the Out cases correctly, it was only able to predict 20% of those who would be in a facility correctly (Table 34). This would explain why the prediction power was greater than that of the significant variables model, but less than that of the NDOC model. The reason the Combination One model was less likely to predict those in the system is due to the fact that it did not include the DUI variable which was more predictive of those in a facility.

Multivariate Model: Combination Two

This model was similar to Combination One, with the addition of DUI to see if the significance would help increase the ability of the model to better predict In versus Out. There was a 7.2% increase in the ability of the model to predict cases correctly.

Adding DUI increased the correct amount of cases predicted to be in a facility to 40% of the time (Table 38). This model suggests that those who commit a DUI related offense are less likely to be out of the system.

Multivariate Model: Combination Three

In this model, the NDOC variables from Combination Two without DUI were utilized; it also included lowest offense score, highest social score, highest total score, number of scores, total number of violations, and total number of discharges. With the addition of the Parole and Probation risk assessment variables, it was found that a person who is out of a facility is more likely to have fewer total scores and a higher offense score, but a lower social and total score. They are also more likely to have more violations and discharges. This model (Table 42) was better at predicting who would be out of a facility, but not much better than the Combination Two model at predicting who would be in a facility. The addition of the Parole and Probation variables did help to predict success.

Multivariate Model: Combination Four

For this final model, the only variables used were number of NDOC IDs, gender, dependent children, gang affiliation, married, number of offenses, number of parole hearings, prior felonies, race white non-white, highest social score, and number of scores. Although this model was still not as predictive as the NDOC model when it came to who would more likely be out of a facility than in, it was one of the more predictive models overall (Table 46). As a side note, this model was run with the addition of DUI offense as well. However, the addition of DUI was more predictive of failure than success and actually decreased the ability of the model to predict success more than the model without the DUI variable (Table 49).

Multivariate Findings of Individual Level Predictors

Overall this study has found that this sample of offenders is not entirely consistent with the literature on individual level factors and their effects on success and failure. In regards to race, the models showed that Caucasians were more likely to be successes rather than minorities, which is consistent with most of the prior literature (Clarke, Yuan-Huei, & Wallace, 1988; Irish, 1989; Piquero, Jennings, Diamond, & Reingle, 2015). However, this may be a reflection of the type of offenders admitted into the program rather than actual success since the majority of offenders in the program were Caucasian (Table 8). It seems that the models were more likely to predict that those out of a facility were male rather than female. This may suggest that female offenders in Nevada are committing similar offenses to males (Adler, 1975; Chesney-Lind & Pasko, 2012; McCoy & Miller, 2013). This is also consistent with the trend in growing female prison populations (Carson & Golinelli, 2013). Conversely, the younger the offender the more likely they were to be out of the system, which is inconsistent with life-course theory (Laub & Sampson, 2003; Ulmer & Steffensmeier, 2014). This suggests that those who are in a facility are older, habitual offenders because they exhibit multiple NDOC IDs and have committed multiple DUIs. However, the models were consistent with life-course theory in that those who were successes were more likely be married and have children (Laub & Sampson, 2003). Yet, offenders were less likely to have a High School Diploma or higher education if they were on parole or out of the system. This is surprising because the majority of the offenders, 70%, had at least a high school diploma or equivalent. The results are consistent with the literature on gang affiliation as those who were considered successes were less likely to be involved in a gang (Dooley et al., 2014; Huebner, Varano, & Bynum, 2007). Regarding prior criminal history, the results were somewhat inconsistent with prior research. Those who had been on parole previously or currently were less likely to be in a facility if they had received a greater number of parole hearings, but they were more likely to have lower risk assessment scores. While an offender can have multiple parole hearings, they only have a limited number of releases (typically one). Therefore, since they are scored when they begin parole, it is probable that most were only paroled once or twice rather than multiple times, which would explain the differences in correlation between these variables. Offenders who were out of a facility were more likely to have higher offense scores, but lower social and total scores. The offense score, which should be reflective of the severity of their current offense, may not be indicative of success upon release, contrary to the findings of Langan and Levin (2002). Lower social and overall total scores are consistent with someone who has their needs met and exhibits less risk than someone with higher scores. Although prisons are seen as criminogenic (Bales & Piquero, 2012; Gendreau, Cullen, & Goggin, 1999; Sampson & Laub, 1993; Spohn & Holleran, 2002; Vieraits, Kvovandzic,& Marvell, 2007), those who were successes were more likely to have had a prior felony, which would have meant they spent time in prison prior to the commission of their most recent offense. It maybe that this sample of offenders have experienced programming in prison on more than one occasion, and these repeated programming opportunities have produced a cumulative impact and have resulted in personal changes.

These findings indicate that the NDOC dataset, which is primarily demographic, is most predictive of success; with the exception of a DUI related offense, which was more predictive of those in a facility. The Parole and Probation data can help predict success to some extent when combined with demographics. But overall, all models were more likely to predict cases would be on parole or out of the system, rather than in a facility. Due to the fact that these models were inaccurately predicting those in the system to be out, it is possible that the variables used are characteristic of both those who are successes and those who are less successful. Therefore, both the NDOC and Parole and Probation variables may not be the best predictors of success or failure.

Limitations

The ability to predict future behavior is a challenge, and it is possible that the limitations to this study reduced the ability to better define who would succeed and who be less likely to succeed upon release. First, the sample size in this study was relatively small, especially when looking at the most predictive models; fewer than 100 cases were included in most of the analyses. This makes it less likely that the findings can be generalized to other offender populations. More participants with less missing data would have increased the prediction power, and these small numbers may explain why many of these findings were inconsistent with previous studies. Second, this sample was taken from a population of offenders who participated in Project Pride, a job readiness program. Those who were placed into the program may have exhibited certain desirable characteristics or traits when compared to those not accepted into the program. This lack of random program selection may have introduced an important bias into the study. Their placement into Project Pride may indicate that they were already more likely to desist from crime upon release, regardless of their criminal history. Third, the ability to predict future behavior is inherently limited. The models at most could only correctly predict placement of 78% of the offenders. Fourth, considering someone on parole or out of the system to be a success may not truly mean that person is successful by other standards. While those on parole must maintain a job and abide by certain rules, they may naturally be less inclined to commit more crime because they are still under supervision. Conversely, those out of the system completely are not supervised, they may have left the area and therefore they may be committing crimes in other locations that that are not known by the creators of these data sets. Fifth, the data used was taken from official records, but many were either nominal or categorical level data, which prevents the use of more rigorous analyses. Also, more variables such as employment status, time to recidivate, and type of recidivism might have provided more information and better analyses to be conducted. Even though the data set and the analyses have their limitations, it was worth conducting this research to get a glimpse into reentry in Nevada.

Implications

It is challenging to predict and place offenders into one or two categories. Each person has unique experiences and persists in crime for different reasons. However, it is worth attempting to understand what factors may influence a person's deviant desire or behavior, especially if that can be changed. This is especially pertinent when the literature shows prisonization produces maladaptive behaviors that negatively affect a person's chances to successfully reintegrate. By understanding what makes a person more likely to succeed once out of prison, only then can effective programming can be developed to reduce the likelihood of recidivism. Nevada's recent interest in rehabilitation and reentry is valid as the cost of warehousing prisoners has soared. This exploratory study is just a stepping-stone to understanding the challenges to effectively assessing an offender's risk and needs here in Nevada. Future research should include larger samples of offenders, and possibly random assignment to create a control group to more effectively discern what factors affect successful reentry.

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Table 1: Original Variables Provided by Agencies

Table 1

Original Variables Provided by Agencies

NDOC
Class #
ID Number
Inmates Name
Gender
Age
Race
Marital Status
Education History
Gang Affiliation
Current Offense
LSI-R Score
Rule Infractions
Commitment Date
Release Date
ID (received, date)
Birth Certificate (received, date)
Job Readiness (referred, completed, date)
Journals (referred, completed, date)
CBT (referred, completed, date)
Employment (Part-Time/Full-Time)
1 month post-release employment
Full-time/Part-time/Same job
Termination Status
Housing Status
New Offense

Parole and Probation
PP Bin Number
Inmates Name
Case #
Offense Score
Social Score
Total PSP Score
Violation Type
Tech Vio Type
Report Date
Discharge Type
Date Terminated

Original Variables Continued

NDOC Website
Gender
Race
Current Custody Level
Current Institution
Current NDOC ID
Number of NDOC IDs
Number of Parole Hearings
Recent Parole Board Hearings
Parole Status
Prior Felonies

Table 2: NDOC Variables Excluded From Analyses

Table 2

NDOC Variables Excluded From Analyses

LSI-R Score
Rule Infractions
Commitment Date
Release Date
ID (received, date)
Birth Certificate (received, date)
Job Readiness (referred, completed, date)
Journals (referred, completed, date)
CBT (referred, completed, date)
Employment (Part-Time/Full-Time)
1 month post-release employment
Full-time/Part-time/Same job
Termination Status
Housing Status
New Offense

Table 3: Original Offense Category Prior to Recoding

Table 3

Original Offense Category Prior to Recoding

Abuse
Allow Children Present Where UCSA Violated
Alter Serial Number on Firearm
Assault w/Deadly Weapon
Attempt Burglary
Attempt Carrying Concealed Weapon
Attempt Conversion of Leased Prop
Attempt Forgery
Attempt Grand Larceny
Attempt Home Invasion
Attempt Larceny
Attempt Obtain Money/Prop Under False Pretense
Attempt Obtain Personal ID Info
Attempt Possess
Attempt Possess Stolen Prop
Attempt Possess Stolen Veh
Attempt Possess CS
Attempt Possess CS for Sale
Attempt Possess CS Schedule 1-4
Attempt Robbery
Attempt Theft
Attempt Transport CS
Attempt Unlawful Possess Financial Lab
Attempted Burglary
Attempted Burglary/Grand Larceny
Attempted Eluding of Police
Attempted Home Invasion
Burglary
Burglary/Possession of Stolen Vehicle
Carrying Concealed Weapon
CGTH Escapee
Child Endangerment
Consp Violate CS Act
Destruction of Prop to Obtain Scrap Metal
DUI
DUI Causing Death
DUI - Causing Death
DUI Casuing Death or SBH
DUI Causing Death
DUI Causing Death of SBH

Note. Words maybe misspelled

Original Offense Category Prior to Recoding Continued
DUI Causing Death or SBH
Embezzlement
Establish Financial Forgery Lab
Ex-Felon Possess Firearm
Fail to Stop on Signal of Peace Officer
False Prescription
Forgery
Fraudulent Use of Credit Cards
Grand Larcemy
Grand Larceny
Grand Larceny - Auto
Grand Larceny Firearm
Grand Larceny Motor Veh
Grand Larceny/Possession of Stolen Vehicle
Habitual Criminal
Habitual Criminal (Lesser)
Insurance Fraud
Larceny
Leaving Scene of Accident
Obtain Money Under False Pretense
Parole Violation
Parole Violation - Instant Offense
PBV
Poss of Firearm by Ex-Felon
Possesion of Controlled Substance
Possess
Possess Stolen Credit Card
Possess Stolen Prop
Possess Stolen Veh
Possess CS
Possess CS for Sale
Possess False ID
Possessin of Firearm by Ex-Felon
Possession of Stolen Vehicle
Probation Violation - Altering Serial Number on Firearm
Probation Violation - Attempted Posession of Stolen Vehicle
Probation Violation - Burglary
Probation Violation - Controlled Substance
Probation Violation - Possession of Stolen Property
Probation Violator - DUI

Notes. Words may be misspelled

Original Offense Category Prior to Recoding Continued
Reckless Driving
Resist Public Officer
Robbery
Sale/Give CS
Theft
Theft and Forgery
Theft from Vending Machine
Traffick CS
Trafficking in a Controlled Substance
Transport CS
Transport of a Controlled Substance
Unlawful Possess Financial Lab
Unlawful Use of CS
Uttering Forged Instrument

Note. Words maybe misspelled

Table 4: Recoding of Categorical Current Offense into Dichotomous Variables

Table 4

Recoding of Categorical Current Offense into Dichotomous Variables

BRG Dichotomous	1 = Charged	2 = Not Charged
CS Dichotomous	0 = Not Charged	1 = Charged
DUI Dichotomous	1 = Charged	2 = Not Charged
FPF Dichotomous	0 = Not Charged	1 = Charged
FRG Dichotomous	0 = Not Charged	1 = Charged
GL Dichotomous	1 = Charged	2 = Not Charged
OTHER Dichotomous	1 = Charged	2 = Not Charged
PSP Dichotomous	0 = Not Charged	1 = Charged
TFT Dichotomous	1 = Charged	2 = Not Charged

Table 5: New Level of Release Variable

Table 5

New Level of Release Variable

Max Prison	1
Close Prison	2
Medium Prison	3
Minimum Prison	4
Minimum Camp	5
Residential Trustee	6
Parole	7
Not in system at all	8

Table 6: Recoding of Categorical Variables into Dichotomous Variables

Table 6

Recoding of Categorical Variables into Dichotomous Variables

Prior Felonies	1 = Yes	2 = No
Gender	2 = Female	3 = Male
Gang Affiliation	1 = No	2 = Yes
Married Dichotomous	2 = Married	3 = Not Married
Dependent Children	1 = No	2 = Yes 1 or More
HSD Dichotomous	1 = No HSD	2 = HSD or Higher
Race White Non-White	1 = White	2 = Non-White
Caucasian Dichotomous	1 = Yes	2 = No
African American Dichotomous	0 = No	1 = Yes
Hispanic Dichotomous	0 = No	1 = Yes
Asian Dichotomous	1 = Yes	2 = No
Other Race Dichotomous	0 = No	1 = Yes

Table 7: Independent Variables Used in Analyses

Table 7

Independent Variables Used in Analyses

Categorical Dichotomous Variables
Prior Felonies
Gender
Gang Affiliation
BRG Dichotomous
CS Dichotomous
DUI Dichotomous
FPF Dichotomous
FRG Dichotomous
GL Dichotomous
OTHER Dichotomous
PSP Dichotomous
TFT Dichotomous
Race White Non-White
Caucasian Dichotomous
African American Dichotomous
Hispanic Dichotomous
Asian Dichotomous
Other Race Dichotomous
Interval Level Variables
Lowest Offense Score
Highest Offense Score
Lowest Social Score
Highest Social Score
Lowest Total Score
Highest Total Score
Recent Total Score
Ratio Level Variables
Age
Number of Offenses
Number of Dependent Children
Total Number of Violations
Total Number of Charges
Number of NDOC IDs
Number of Parole Hearings
Number of Risk Assessment Scores

Table 8: Age of Offenders

Table 8

Age of Offenders

Mean	38.40
Median	38.00
Mode	31
Range	52
Minimum	20
Maximum	72

Table 9: Breakdown of Gender

Table 9

Breakdown of Gender

Gender	Frequency	Percent	Cumulative Percent
Female	78	19.4	19.4
Male	325	80.6	100.0
Total	403	100.0	–

Table 10: Breakdown of Race

Table 10

Breakdown of Race

Race	Frequency	Percent	Cumulative Percent
Caucasian	231	57.3	57.3
African American	114	28.3	85.6
Hispanic	42	10.4	96.0
Asian	10	2.5	98.5
Other	6	1.5	100.0
Total	403	100.0	–

Note. Other = American Indian or Native American

Table 11: Marital Status

Table 11

Marital Status

Status	Frequency	Valid Percent	Cumulative Percent
Single	67	66.3	66.3
Married	17	16.8	83.2
Divorced	9	8.9	92.1
Separated	5	5.0	97.0
Widowed	3	3.0	100.0
Total	101	100.0	–

Note. Missing cases = 302

Table 12: Dependent Children

Table 12

Number of Dependent Children

Number of Dependent Children	Frequency	Valid Percent	Cumulative Percent
0	139	35.9	35.9
1	73	18.9	54.8
2	68	17.6	72.4
3	49	12.7	85.0
4	35	9.0	94.1
5	11	2.8	96.9
6	8	2.1	99.0
7	2	.5	99.5
8	2	.5	100.0
Total	387	100.0	–

Note. Missing cases = 16

Table 13: Education History

Table 13

Education History

Education Level	Frequency	Valid Percent	Cumulative Percent
Some High School	114	29.3	29.3
High School Diploma/GED	239	61.4	90.7
Some College	17	4.4	95.1
College Degree	19	4.9	100.0
Total	389	100.0	–

Note. Missing cases = 14

Table 14: Gang Affiliation

Table 14

Gang Affiliation

Gang Affiliated	Frequency	Valid Percent	Cumulative Percent
No	316	80.8	80.8
Yes	75	19.2	100.0
Total	391	100.0	–

Note. Missing cases = 14

Table 15: Prior Felonies

Table 15

Prior Felonies

Prior Felonies	Frequency	Percent	Cumulative Percent
No	114	28.3	28.3
Yes	289	71.7	100.0
Total	403	100.0	–

Table 16: Level of Release

Table 16

Level of Release

Level of Release	Frequency	Percent	Cumulative Percent
Max Prison	1	.2	.2
Close Prison	8	2.0	2.2
Medium Prison	39	9.7	11.9
Minimum Prison	21	5.2	17.1
Minimum Camp	24	6.0	23.1
Residential Trustee	6	1.5	24.6
Parole	84	20.8	45.4
Not in system at all	220	54.6	100.0
Total	403	100.0	–

Table 17: Offense Category Breakdown

Table 17

Offense Category Breakdown

Type of Offense	Frequency	Percent	Cumulative Percent
CS = Controlled Substance Related	76	18.9	18.9
DUI = DUI Related	50	12.4	31.3
FPF = Felon Poss Firearms Related	18	4.5	35.7
FRG = Forgery Related	14	3.5	39.2
BRG = Burglary Related	91	22.6	61.8
GL = Larceny/Grand Larceny Related	33	8.2	70.0
OTHER = Other Related	64	15.9	85.9
PSP = Poss of Stolen Prop Related	39	9.7	95.5
TFT = Theft	18	4.5	100.0
Total	403	100.0	–

Table 18: Bivariate Correlation Variables

Table 18

Bivariate Correlation Variables

1. Lowest Offense Score
2. Highest Offense Score
3. Lowest Social Score
4. Highest Social Score
5. Lowest Total Score
6. Highest Total Score
7. Recent Total Score
8. Number of Total Scores
9. Number of Offenses
10. Number of NDOC IDs
11. Number of Parole Hearings
12. Prior Felonies
13. Gender
14. Age
15. Caucasian Race Dichotomous Variable
16. African American Race Dichotomous Variable
17. Hispanic Race Dichotomous Variable
18. Asian Race Dichotomous Variable
19. Other Race Dichotomous Variable
20. Dependent Children
21. Gang Affiliation
22. Burglary Dichotomous Variable
23. Controlled Substance Dichotomous Variable
24. DUI Current Dichotomous Variable
25. Felon Poss of Firearm Charge Dichotomous Variable
26. Forgery Charge Dichotomous Variable
27. Larceny Dichotomous Variable
28. Other Offense Dichotomous Variable
29. Possession Stolen Property Dichotomous Variable
30. Theft Dichotomous Variable
31. Level of Release
32. In/Out
33. Total Number of Violations
34. Total Number of Charges
35. Race White Non White Dichotomous Variable
36. Marital Status Dictomous Var
37. High School Degree Dich Variable

Note. Numbers 31 and 32 are dependent variables

Table 19: Bivariate Correlations Significance Results

Table 19

Point Biserial Correlation Significance Results

Independent Variables	Dependent Variable
	In/Out
Lowest Offense Score	.126*
Highest Social Score	-.163**
Highest Total Score	-.108*
Number of Total Scores	-.106*
Number of NDOC IDs	-.114*
Number of Parole Hearings	-.118*
CS Dichotomous Variable	.113*
DUI Dichotomous Variable	.187**
Forgery Dichotomous Variable	.108*

Note. * = p < .05, ** = p < .01

Table 20: Significant Variables Null Classification Table

Table 20

Significant Variables Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	89	.0
Out of all Facilities	0	280	100.0
Overall Percentage	–	–	75.9

Table 21: Significance of Variables Not in Model

Table 21

Significance of Variables Not in Model

LowestOffense	.016*
HighestSocial	.002**
HighestTotal	.038*
NumberOfScores	.039*
NumOfNDOCIDs	.031*
NumOfParoleHear	.053
ControlledSubstDichVar	.068
DUIDichVar	.000**
ForgeryDichVar	.032*
Overall Statistics	.000**

Note. * = p < .05, ** = p < .01

Table 22: Significant Variables Model Classification Table

Table 22

Significant Variables Model Classification Table

Observed	Predicted: In a Facility	Predicted: Out of all Facilities	Percentage Correct
In a Facility	6	83	6.7
Out of all Facilities	6	274	97.9
Overall Percentage	–	–	75.9

Table 23: Logistic Regression with Significant Variables

Table 23

Logistic Regression with Significant Variables

IV	B	S.E.	Wald	df	Sig.	Exp(B)
LowestOffense	.030	.020	2.340	1	.126	1.030
HighestSocial	-.021	.034	.397	1	.529	.979
HighestTotal	-.007	.015	.207	1	.649	.993
NumberOfScores	.058	.130	.198	1	.657	1.059
NumOfNDOCIDs	-.097	.341	.080	1	.777	.908
NumOfParoleHear	-.131	.095	1.913	1	.167	.877
ControlledSubstDichVar	.453	.375	1.459	1	.227	1.572
DUIDichVar	1.380	.371	13.809	1	.000**	3.976
ForgeryDichVar	19.833	10560.012	.000	1	.999	410345328.860
Constant	-.900	1.174	.587	1	.443	.407

Note. IV = Independent Variable, B = Logistic Coefficient, S.E. = Standard Error, Wald = Test of Significance Score, df = Degrees of Freedom, Sig. = Significance, Exp(B) = Exponent of the Logistic Coefficient or Odds Ratio, ** = p < .01

Table 24: NDOC Null Classification Table

Table 24

NDOC Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	33	.0
Out of all Facilities	0	65	100.0
Overall Percentage	–	–	66.3

Table 25: Significance of NDOC Variables Not in Model

Table 25

Significance of NDOC Variables Not in Model

NumOfNDOCIDs	.514
Gender	.252
Age	.508
DependentChildren	.171
GangAffiliation	.450
MarriedDichVar	.723
NumberOfOffenses	.740
NumOfParoleHear	.616
ControlledSubstDichVar	.295
DUIDichVar	.001**
HSDDichVar	.339
PriorFelonies	.677
RaceWhiteNonWhite	.937
BurglaryDichVar	.830
FelonPossFirearmDichVar	.363
ForgeryDichVar	.072
LarcenyDichVar	.985
OtherOffDichVar	.497
PossStolPropDichVar	.260
TheftDichVar	.382

Note. ** = $p < .01$

Table 26: NDOC Model Classification Table

Table 26

NDOC Model Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	18	15	54.5
Out of all Facilities	6	59	90.8
Overall Percentage	–	–	78.6

Table 27: Logistic Regression with NDOC Variables

Table 27

Logistic Regression with NDOC Variables

IV	B	S.E.	Wald	df	Sig.	Exp(B)
NumOfNDOCIDs	-.721	.735	.962	1	.327	.486
Gender	1.193	.622	3.676	1	.055	3.298
Age	-.001	.029	.000	1	.985	.999
DependentChildren	.682	.561	1.477	1	.224	1.977
GangAffiliation	-.632	.824	.587	1	.443	.532
MarriedDichVar	-.034	.726	.002	1	.962	.966
NumberOfOffenses	.032	.700	.002	1	.964	1.032
NumOfParoleHear	.016	.272	.003	1	.954	1.016
ControlledSubstDichVar	1.338	1.251	1.144	1	.285	3.811
DUIDichVar	.754	1.120	.454	1	.501	2.126
HSDDichVar	-.500	.613	.666	1	.414	.606
PriorFelonies	-.129	.744	.030	1	.862	.879
RaceWhiteNonWhite	-.583	.597	.955	1	.328	.558
BurglaryDichVar	-.918	1.174	.610	1	.435	.399
FelonPossFirearmDichVar	1.644	1.557	1.115	1	.291	5.174
ForgeryDichVar	21.313	16208.200	.000	1	.999	1803223027.873
LarcenyDichVar	-.660	1.368	.232	1	.630	.517
OtherOffDichVar	-1.367	1.283	1.134	1	.287	.255
PossStolPropDichVar	2.175	1.584	1.886	1	.170	8.802
Constant	3.727	8.262	.204	1	.652	41.559

Note. IV = Independent Variable, B = Logistic Coefficient, S.E. = Standard Error, Wald = Test of Significance Score, df = Degrees of Freedom, Sig. = Significance, Exp(B) = Exponent of the Logistic Coefficient or Odds Ratio

Table 28: Parole and Probation Classification Table

Table 28

Parole and Probation Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	31	.0
Out of all Facilities	0	117	100.0
Overall Percentage	–	–	79.1

Table 29: Significance of Parole and Probation Variables Not in Model

Table 29

Significance of Parole and Probation Variables Not in Model

LowestOffense	.349
HighestOffense	.356
LowestSoc	.454
HighestSocial	.370
LowestTotal	.821
HighestTotal	.975
RecentTotal	.798
NumberOfScores	.633
TotalNumOfViol	.506
TotalNumOfDischarges	.213

Table 30: Parole and Probation Model Classification Table

Table 30

Parole and Probation Model Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	2	29	6.5
Out of all Facilities	0	117	100.0
Overall Percentage	–	–	80.4

Table 31: Logistic Regression with Parole and Probation Variables

Table 31

Logistic Regression with Parole and Probation Variables

IV	B	S.E.	Wald	df	Sig.	Exp(B)
LowestOffense	-11.884	11063.335	.000	1	.999	.000
HighestOffense	18.957	11703.198	.000	1	.999	170914948.173
LowestSoc	64.759	30977.608	.000	1	.998	13325690795684268000000000000.000
HighestSocial	-57.773	30061.523	.000	1	.998	.000
LowestTotal	55.005	36935.919	.000	1	.999	773553380218151300000000.000
HighestTotal	7.898	6132.981	.000	1	.999	2690.734
RecentTotal	-69.931	41240.994	.000	1	.999	.000
NumberOfScores	20.211	27489.968	.000	1	.999	599421776.743
TotalNumOfViol	.371	.824	.203	1	.652	1.450
TotalNumOfDischarges	.610	.592	1.064	1	.302	1.841
Constant	-19.380	27489.968	.000	1	.999	.000

Note. IV = Independent Variable, B = Logistic Coefficient, S.E. = Standard Error, Wald = Test of Significance Score, df = Degrees of Freedom, Sig. = Significance, Exp(B) = Exponent of the Logistic Coefficient or Odds Ratio

Table 32: Combination One Null Classification Tables

Table 32

Combination One Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	33	.0
Out of all Facilities	0	65	100.0
Overall Percentage	–	–	66.3

Table 33: Significance of Combination One Variables Not in Model

Table 33

Significance of Combination One Variables Not in Model

NumOfNDOCIDs	.514
NumberOfOffenses	.740
NumOfParoleHear	.616
PriorFelonies	.677
Gender	.252
Age	.508
DependentChildren	.171
GangAffiliation	.450
MarriedDichVar	.723
HSDDichVar	.339
RaceWhiteNonWhite	.937

Table 34: Combination One Model Classification Table

Table 34

Combination One Model Classification Table

Observed	Predicted: In a Facility	Predicted: Out of all Facilities	Percentage Correct
In a Facility	7	26	21.2
Out of all Facilities	6	59	90.8
Overall Percentage	–	–	67.3

Table 35: Logistic Regression with Combination One Variables

Table 35

Logistic Regression with Combination One Variables

IV	B	S.E.	Wald	df	Sig.	Exp(B)
NumOfNDOCIDs	-1.112	.695	2.560	1	.110	.329
NumberOfOffenses	.221	.516	.183	1	.669	1.247
NumOfParoleHear	.209	.234	.801	1	.371	1.233
PriorFelonies	-.630	.586	1.158	1	.282	.533
Gender	.877	.550	2.539	1	.111	2.403
Age	-.020	.025	.658	1	.417	.980
DependentChildren	.896	.514	3.036	1	.081	2.449
GangAffiliation	-.153	.707	.047	1	.829	.858
MarriedDichVar	.385	.661	.339	1	.560	1.470
HSDDichVar	-.302	.540	.313	1	.576	.739
RaceWhiteNonWhite	-.449	.495	.822	1	.364	.638
Constant	-.418	3.440	.015	1	.903	.659

Note. IV = Independent Variable, B = Logistic Coefficient, S.E. = Standard Error, Wald = Test of Significance Score, df = Degrees of Freedom, Sig. = Significance, Exp(B) = Exponent of the Logistic Coefficient or Odds Ratio

Table 36: Combination Two Null Classification Table

Table 36

Combination Two Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	33	.0
Out of all Facilities	0	65	100.0
Overall Percentage	–	–	66.3

Table 37: Significance of Combination Two Variables Not in Model

Table 37

Significance of Combination Two Variables Not in Model

NumOfNDOCIDs	.514
Gender	.252
Age	.508
DependentChildren	.171
GangAffiliation	.450
MarriedDichVar	.723
NumberOfOffenses	.740
NumOfParoleHear	.616
DUIDichVar	.001**
HSDDichVar	.339
PriorFelonies	.677
RaceWhiteNonWhite	.937

Note. ** = $p < .01$

Table 38: Combination Two Model Classification Table

Table 38

Combination Two Model Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	13	20	39.4
Out of all Facilities	6	59	90.8
Overall Percentage	–	–	73.5

Table 39: Logistic Regression with Combination Two Variables

Table 39

Logistic Regression with Combination Two Variables

IV	B	S.E.	Wald	df	Sig.	Exp(B)
NumOfNDOCIDs	-.848	.687	1.526	1	.217	.428
Gender	1.057	.588	3.228	1	.072	2.877
Age	-.009	.026	.136	1	.713	.991
DependentChildren	.754	.537	1.975	1	.160	2.126
GangAffiliation	-.188	.743	.064	1	.800	.828
MarriedDichVar	.173	.711	.059	1	.808	1.189
NumberOfOffenses	.264	.564	.218	1	.640	1.302
NumOfParoleHear	.033	.231	.020	1	.886	1.034
DUIDichVar	1.980	.651	9.236	1	.002**	7.242
HSDDichVar	-.464	.571	.660	1	.416	.629
PriorFelonies	-.052	.654	.006	1	.936	.949
RaceWhiteNonWhite	-.848	.552	2.361	1	.124	.428
Constant	-3.824	3.781	1.023	1	.312	.022

Note. IV = Independent Variable, B = Logistic Coefficient, S.E. = Standard Error, Wald = Test of Significance Score, df = Degrees of Freedom, Sig. = Significance, Exp(B) = Exponent of the Logistic Coefficient or Odds Ratio, ** = $p < .01$

Table 40: Combination Three Null Classification Table

Table 40

Combination Three Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	29	.0
Out of all Facilities	0	62	100.0
Overall Percentage	–	–	68.1

Table 41: Significance of Combination Three Variables Not in Model

Table 41

Significance of Combination Three Variables Not in Model

LowestOffense	.839
NumOfNDOCIDs	.747
NumberOfOffenses	.410
NumOfParoleHear	.563
PriorFelonies	.600
Gender	.311
Age	.523
DependentChildren	.137
GangAffiliation	.559
TotalNumOfViol	.749
TotalNumOfDischarges	.580
RaceWhiteNonWhite	.673
MarriedDichVar	.737
HSDDichVar	.455
HighestSocial	.018*
HighestTotal	.017*
NumberOfScores	.497

Note. * = $p < .05$

Table 42: Combination Three Model Classification Table

Table 42

Combination Three Model Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	12	17	41.4
Out of all Facilities	4	58	93.5
Overall Percentage	–	–	76.9

Table 43: Logistic Regression with Combination Three Variables

Table 43

Logistic Regression with Combination Three Variables

IV	B	S.E.	Wald	df	Sig.	Exp(B)
LowestOffense	.024	.041	.333	1	.564	1.024
NumOfNDOCIDs	-.339	.843	.162	1	.687	.712
NumberOfOffenses	.576	.665	.750	1	.386	1.779
NumOfParoleHear	.137	.283	.237	1	.627	1.147
PriorFelonies	-.645	.657	.965	1	.326	.524
Gender	1.055	.659	2.561	1	.110	2.872
Age	-.006	.029	.042	1	.838	.994
DependentChildren	1.167	.590	3.913	1	.048	3.211
GangAffiliation	-.313	.791	.156	1	.693	.732
TotalNumOfViol	-.112	.780	.021	1	.886	.894
TotalNumOfDischarges	-.090	.415	.046	1	.829	.914
RaceWhiteNonWhite	-.619	.554	1.247	1	.264	.539
MarriedDichVar	.379	.767	.244	1	.621	1.461
HSDDichVar	-.070	.631	.012	1	.912	.933
HighestSocial	-.028	.084	.108	1	.742	.973
HighestTotal	-.038	.038	1.006	1	.316	.963
NumberOfScores	.098	.341	.083	1	.773	1.103
Constant	-.484	4.162	.014	1	.907	.616

Note. IV = Independent Variable, B = Logistic Coefficient, S.E. = Standard Error, Wald = Test of Significance Score, df = Degrees of Freedom, Sig. = Significance, Exp(B) = Exponent of the Logistic Coefficient or Odds Ratio

Table 44: Combination Four Null Classification Table

Table 44
Combination Four Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	30	.0
Out of all Facilities	0	62	100.0
Overall Percentage	–	–	67.4

Table 45: Significance of Combination Four Variables Not in Model

Table 45

Significance of Combination Four Variables Not in Model

NumOfNDOCIDs	.815
Gender	.366
DependentChildren	.104
GangAffiliation	.511
MarriedDichVar	.788
NumberOfOffenses	.378
NumOfParoleHear	.494
PriorFelonies	.674
RaceWhiteNonWhite	.778
HighestSocial	.025*
NumberOfScores	.574

Note. * = $p < .05$

Table 46: Combination Four Model Classification Table

Table 46

Combination Four Model Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	13	17	43.3
Out of all Facilities	4	58	93.5
Overall Percentage	–	–	77.2

Table 47: Logistic Regression with Combination Four Variables

Table 47

Logistic Regression with Combination Four Variables

IV	B	S.E.	Wald	df	Sig.	Exp(B)
NumOfNDOCIDs	-.272	.780	.122	1	.727	.762
Gender	.914	.614	2.216	1	.137	2.493
DependentChildren	1.021	.539	3.592	1	.058	2.777
GangAffiliation	-.173	.709	.060	1	.807	.841
MarriedDichVar	.132	.723	.033	1	.855	1.141
NumberOfOffenses	.691	.617	1.256	1	.262	1.996
NumOfParoleHear	.111	.251	.195	1	.658	1.117
PriorFelonies	-.487	.592	.675	1	.411	.615
RaceWhiteNonWhite	-.544	.523	1.085	1	.298	.580
HighestSocial	-.090	.048	3.567	1	.059	.914
NumberOfScores	-.037	.261	.020	1	.888	.964
Constant	-.046	3.185	.000	1	.988	.955

Note. IV = Independent Variable, B = Logistic Coefficient, S.E. = Standard Error, Wald = Test of Significance Score, df = Degrees of Freedom, Sig. = Significance, Exp(B) = Exponent of the Logistic Coefficient or Odds Ratio

Table 48: Risk Assessment Correlations

Table 48

Spearman's Rho Risk Assessment Score Correlations

Variable	1	2	3	4	5	6	7
1. Lowest Offense Score N=369	–	–	–	–	–	–	–
2. Highest Offense Score N=369	.166**	–	–	–	–	–	–
3. Lowest Social Score N=369	.417**	-.075	–	–	–	–	–
4. Highest Social Score N=369	-.246**	.417**	.269**	–	–	–	–
5. Lowest Total Score N=369	.840**	.112*	.750**	.006	–	–	–
6. Highest Total Score N=369	.162**	.868**	.208**	.697**	.244**	–	–
7. Recent Total Score N=148	.839**	.739**	.705**	.638**	.999**	.913**	–
8. Number of Total Scores N=369	-.574**	.441**	-.470**	.501**	-.561**	.417**	-.089

Note. Correlation Coefficients, * = p < .05, ** = p < .01

Table 49: Combination Four Classification Tables with DUI Variable

Table 49a

Combination Four with DUI Null Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	0	30	.0
Out of all Facilities	0	62	100.0
Overall Percentage	–	–	67.4

Table 49b

Combination Four with DUI Model Classification Table

	Predicted		
Observed	In a Facility	Out of all Facilities	Percentage Correct
In a Facility	14	16	46.7
Out of all Facilities	7	55	88.7
Overall Percentage	–	–	75.0