2009

A Validation study of Risk Management Systems

Bridget Kelly
University of Nevada, Las Vegas

A VALIDATION STUDY OF RISK MANAGEMENT SYSTEMS

by

Bridget Kelly

Bachelor of Arts
University of Nevada, Las Vegas
2007

A thesis submitted in partial fulfillment
of the requirements for the

Master of Arts Degree in Criminal Justice
Department of Criminal Justice
Greenspun College of Urban Affairs

Graduate College
University of Nevada, Las Vegas
December 2009

THE GRADUATE COLLEGE

We recommend that the thesis prepared under our supervision by

Bridget Kelly

entitled

A Validation Study of Risk Management Systems

be accepted in partial fulfillment of the requirements for the degree of

Master of Arts
Criminal Justice

Joel D. Lieberman, Committee Chair

Deborah K. Shaffer, Committee Member

Hong Lu, Committee Member

Stacey Hardy-Desmond, Graduate Faculty Representative

Ronald Smith, Ph. D., Vice President for Research and Graduate Studies
and Dean of the Graduate College

December 2009

ABSTRACT

A Validation Study of Risk Management Systems
by

Bridget Kelly

Dr. Joel Lieberman, Committee Chair
Associate Professor of Criminal Justice
University of Nevada, Las Vegas

The purpose of this study was to examine the predictive validity of Risk Management Systems (RMS) as a risk assessment instrument. To date, a published validation study does not exist for the RMS. The study employs secondary data analysis to examine the predictive validity of RMS recidivism and violence scores on three outcomes: arrest, unsuccessful termination from supervision, and technical violations. The study sample consisted of 830 probationers from the United States Probation Office, District of Nevada. The analyses showed that RMS recidivism and violence scores were moderately predictive of all three outcomes.

ACKNOWLEDGEMENTS

This thesis has been one of the biggest challenges I have faced in life, the completion of which would not have been possible without support and guidance from many. First, I would like to thank Dr. Deborah Koetzle Shaffer and Dr. Joel D. Lieberman for their time and guidance throughout the course of this study. I am also grateful to my committee members, Dr. Hong Lu and Dr. Hardy-Desmond for their advice. I would like to thank the U.S. Probation, District of Nevada, Las Vegas office for providing data and assistance along the way. I would also like to thank Brian Brehman, whose moral and technical support saved the day many times. Many thanks to my family are in order, for their companionship and for making sure I eat real food. Finally, I would like to thank Keiki for her unconditional love and patience, and for being the sunshine of my life.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

The criminal justice system relies on community supervision to deal with the large numbers of offenders that are released or diverted from incarceration. Currently, this component of the corrections system allows offenders to function as community members while ensuring that their needs are monitored and managed by officers that have dual law enforcement and social worker functions. According to the Bureau of Justice Statistics (2008), 2.9 million people entered community supervision in the United States in 2007. The federal probation caseload consisted of 23,450 offenders at year end 2007; the parole caseload consisted of 88,993 offenders (Bureau of Justice Statistics, 2008). With a daily cost of $9.92 for community supervision versus $68.28 per day of incarceration for federal offenders in 2007 (U.S. Courts, 2008), community supervision is a necessary function for processing criminal offenders using limited resources.

To achieve efficiency, supervising agencies generally classify their offender populations into subgroups for purposes of supervision and treatment. Research has demonstrated support for the effectiveness of offender classification at predicting likelihood of recidivism. Consequently, it is possible to have discrimination in service provision by offender type (Gendreau, Cullen, & Bonta, 1994). By identifying offenders as being at low, medium, or high risk for recidivating, appropriate supervision and treatment services can be provided at levels that are effective and reduce expenditure. In essence, classification provides a guide to targeting high-risk offenders with more resources and avoiding a waste of those resources on lower-risk populations of offenders who are a lesser threat to the community.

In order to make the best use of limited resources while protecting public safety, correctional agencies often use risk assessment instruments to classify offenders by their risk of recidivism. Risk assessments act as a guide for the designation of offenders to varying levels of supervision and treatment, and are integral tools in case management (Girard & Wormith, 2004; Harris, 1994; Lowencamp, Holsinger, & Latessa, 2001). Assessments are designed to identify the presence of factors associated with criminal behavior and weight those factors, in order to provide practitioners with information regarding risk level and needs for service referral.

Risk assessment instrument accuracy is critical for predicting future criminal behavior to maximize correctional functioning while upholding the best interests of the offender and community (Bonta, 2002). If agencies are to rely on an instrument to guide supervision and case planning, the instrument must be valid and reliable. Failure to accurately identify risk could result in unsuccessful case planning, which could lead to higher recidivism rates among the population supervised in the community. In addition, when supervision fails by means of recidivism, resources are exhausted in vain. Therefore it is essential that risk assessment instruments are validated by research.

The current study will examine the predictive validity of Risk Management Systems (RMS), the risk assessment instrument used by United States Probation Office, District of Nevada for classification of offenders. RMS risk and violence scores are used by USPO in case planning for assistance in determining level of intensity in supervision and service delivery. Published research examining the predictive validity of the RMS does not currently exist; therefore, the current research may prove useful by providing insight into this matter.

CHAPTER 2

LITERATURE REVIEW

Risk Prediction and Classification

To predict recidivism for the classification of offenders, corrections agencies may use a variety of standardized assessment instruments. These instruments may come in different formats including checklists, interviews, and self-administered questionnaires, "which characterize the offender's social, demographic, and criminal history" (Van Voorhis, 2000, p. 82). Typically, when an offender is initially placed under supervision, the offender is classified using a risk assessment instrument based on a typology ("type" based on research, usually criminogenic needs) that is administered by trained staff in a consistent manner. Once assessed, offenders are classified into subgroups based on risk level and assigned to associated levels of supervision and service provision, consistent with the "risk principle" of effective intervention (Gendreau, 1996; Harris, 1994; Van Voorhis, 2000).

The "risk principle" assumes that criminal behavior can be predicted. This assumption is supported when studies are able to identify risk factors that correlate with criminal behavior. After the risk level of an offender is determined, treatment services are provided that are most effective when they are delivered at a level matching the risk level of the offender (i.e. high risk offenders should receive intense treatment while low risk offenders are in need of less intense treatment). Intensity of service delivery has been found by Gendreau to be a "principle of effective intervention" (1996). Through behavioral therapy, further anti-social behavior (recidivism) can be decreased (Gendreau, 1996). The process of matching interventions appropriately with changing risk levels in an effort to decrease risk of recidivism is referred to as “risk management” (Epperson, Ralston, Fowler, & DeWitt, 2006). Research shows that intensive services provided to high-risk offenders are associated with a much higher decrease in recidivism than intensive services provided to low-risk offenders (Andrews & Bonta, 2006; Van Voorhis, 2000). Research also indicates that intensive services provided to low-risk offenders may actually be detrimental, as this inappropriate level of service has been correlated with higher rates of recidivism among the lower-risk groups (Bonta, 2002; Bonta, Wallace-Capretta, & Rooney, 2000). This is said to be due to exposure to criminal peers and attitudes during treatment, as treatment is often provided in a group setting.

Assessment of Violent Risk

Several researchers have noted the difficulty predicting violence compared to general recidivism (Dolan & Doyle, 2000; Gendreau, Little, & Goggin, 1996), and attributed this difficulty to the relatively lower base rates of violent behavior as well as the possibility that fewer factors predict the wide variations in violent crime. Prediction of violent behavior is not unlike prediction of other recidivism in that some of the same risk factors can be used (Gendreau, Little, & Goggin, 1996). Risk factors such as psychopathy and criminal history are noted risk factors of violent behavior, and can be detected with indicators such as impulsivity, and history of aggression against other people. Although assessment instruments specifically designed to detect psychopathy and violent behavior have been validated for accuracy, Gendreau, Little, and Goggin (1996) maintain that a general risk assessment may be just as effective if many dynamic risk factors are included. Douglas and Skeem (2005) stress the importance of detecting “risk state" through dynamic risk factors that may indicate changes at the individual level that affect likelihood of behaving violently. Impulsiveness, negative affectivity (i.e. anger, negative mood), psychosis, antisocial attitudes, substance abuse, interpersonal relationships, and treatment alliance and adherence have all been suggested as dynamic risk factors to be used in violence assessment (Douglas & Skeem, 2005), consistent with general recidivism prediction research.

Risk Factors

Risk of recidivism is best determined by numerous indicators that are predictive of recidivism, or risk factors (Andrews & Bonta, 2006; Gendreau, 1996; Glover, Nicholson, Hemmati, Bernfeld, & Quinsey 2002; Kleiman, Ostrom, & Cheesman 2007; Lowencamp, Holsinger, & Latessa, 2001). An offender's risk factors are identified through risk assessment, conducted with a standardized measurement instrument. The presence or absence of risk factors determines risk level, thereby allowing supervision and services to be delegated according to priority. Research has identified the most common risk factors to be used for the prediction of criminal behavior and classification by risk level.

"The Big Four" are the primary four factors found to be predictive of criminal behavior (Andrews & Bonta, 2006, Bonta, 2002). Included in the "Big Four" are: criminal history, antisocial personality, antisocial attitudes, and social support for crime. Although criminal history is a static factor and will not change with treatment, therapy can help offenders to identify the other factors and change them by applying techniques learned in treatment. Identification of risk factors is important for the appropriate designation of rehabilitative services, as discussed using the risk principle (Andrews & Bonta, 2006).

Offenders are classified and/or assigned to treatment programs based on their criminogenic needs, which are identified through risk assessment. Risk assessment measures the presence of criminogenic needs to predict future criminal behavior (recidivism). Accurate risk assessments are especially important in order to treat offenders based on need, and are found when there are "statistically significant associations between predictors…and the criterion (criminal behavior measured…)" (Andrews & Bonta, 2006, p. 271). Assessment instruments should seek to identify and utilize "relevant variables" to predict recidivism by identifying risk, and "to guide the intensity [and nature] of treatment" (Andrews & Bonta, 2006).

The need principle suggests that certain dynamic risk factors are associated with criminal behavior and "when changed, are associated with changes in the probability of recidivism" (Andrews & Bonta, 2006, p. 281). These risk factors are also referred to as criminogenic needs, several of which have been identified by research. The "Central Eight factors" are criminogenic needs found to be predictive of criminal behavior. They include: "criminal history, antisocial personality pattern, antisocial attitudes, employment and education problems, family and marital problems, lack of prosocial leisure pursuits, substance abuse, personal aptitudes, and high crime neighborhood" (Andrews & Bonta, 2006: pp. 277). Criminogenic needs should be targeted in treatment of offenders in an effort to reduce recidivism. This is done by referring offenders to services that will meet their individual needs, such as education, job and skill building, counseling for substance abuse, mental health, or relationships, and others. By targeting these needs with services designed to help the offender transition into a conventional lifestyle, treatment indirectly impacts recidivism, as criminal behavior is often not conducted in an arena where it can be directly prevented. Changes in criminogenic needs are therefore the "intermediate goals of treatment," in that those changes are a needed element in reducing recidivism (Andrews & Bonta, 2006).

Development of Risk Assessment

Prior to the use of structured risk assessment instruments, practitioners made judgments about risk based on their own experiences and intuition. The use of professional (clinical) judgment to determine risk of recidivism is referred to as "first generation risk assessment." Research has found first generation risk assessment to be inferior to objective and structured methods of prediction (Grove & Meehl, 1996; Grove, Zald, Lebow, Snitz, & Nelson, 2000). Grove et al (2000) conducted a meta-analysis of 136 studies regarding the prediction of human behavior and health diagnoses and found only 8 of the studies demonstrated more favorable accuracy for clinical judgments over empirically based risk assessment.

Unstructured clinical judgments are inadequate for a number of reasons, including ignorance of baseline recidivism rates, weighting of factors inconsistent with research, and classification based on "preconceived categories" ("employing the representativeness heuristic," or using knowledge or previous experiences to infer similarity to the current situation or person being assessed) (Andrews & Bonta, 2006; Bonta 2002; Krauss & Lieberman, 2007). For example, clinicians who have worked with substance abusers may view substance abuse as more or less associated with criminal behavior depending on their own experience with clientele, and as such assign weight to this variable at a different level than would be found in empirical research. These limitations to unstructured clinical judgments contribute to the potential for inaccuracy and unreliability in risk prediction. Research on the accuracy of "future dangerousness" testimony by psychiatrists, for example, demonstrates an error rate of 65 to 85% (Krauss & Lieberman, 2007; Monohan, 1981).

Risk assessment accuracy has improved with the development of standardized instruments that utilize actuarial measures predictive of criminality (Andrews, Bonta, & Wormith, 2006). The "second generation" (2G) of risk assessment is characterized by the simple use of predictive factors that have been found through empirical research. The factors utilized in the 2G risk assessment are static, meaning that they cannot be changed. Static risk factors include but are not limited to: criminal history, age at time of assessment, and gender. The Psychopathy Checklist-Revised (PCL-R) and the Violence Risk Appraisal Guide (VRAG) are commonly used 2G instruments that have been validated in research.

As indicated by its name, the Psychopathy Checklist-Revised screens for psychopathy and is sometimes used with criminal offenders for risk assessment (Gendreau, Goggin, & Smith, 2002). Hare, the creator of the PCL-R, has conducted research that indicates that psychopathy is an important predictor of recidivism, particularly violent recidivism (Hare, 1998). Practitioners using the PCL-R conduct semi-structured interviews, review case history, and behavioral observation as needed to assess the offender for symptoms of psychopathy by rating 20 items including personality traits (such as use of manipulation, callousness, lack of remorse, grandiosity), as well as behavioral traits (such as impulsivity, juvenile delinquency, and poor behavioral control). Although the PCL-R is supposed to serve as a diagnostic and not a risk prediction instrument (Hemphill & Hare 2004), the instrument does measure antisocial personality and antisocial behavior, addressing two of the “Big Four” risk factors (Andrews, Bonta, & Wormith, 2006).

The Violence Risk Appraisal Guide (VRAG) includes the PCL-R as well as 11 other items that review historical information including details of the current offense in its content, and is used to predict violent recidivism. Both the PCL-R and the VRAG have been shown to have predictive validity for general and violent recidivism, although research is conflicting as to whether either instrument is superior to the other in prediction of violent recidivism (Bonta, 2002; Glover, Nicholson, Hemmati, Bernfeld, & Quinsey, 2002).

A criticism of 2G risk assessment is that these type of instruments are composed only of static risk factors and are not intentionally based in theory (Andrews, Bonta, & Wormith, 2006). Because 2G instruments include only a few of the major risk factors, more comprehensive measures are needed to assess risk. Dynamic risk factors, those which are amenable to change over time, should be included in risk assessment. Dynamic risk factors are not only good predictors of criminal behavior (Andrews & Bonta, 2006), they are also useful targets for intervention and can be used to measure changes in risk level. Utilizing several actuarial (research-based) domains in an assessment allows for the identification of varied factors that are correlated with criminal behavior (Andrews & Bonta, 2006).

Risk factor domains can be categorized by underlying criminological theories, including sociological, social learning, and psychopathological theories (Andrews & Bonta, 2006). Sociological theories link crime to the social, economic, and political environment. Examples of sociological theories include strain theory, social control theory, and social learning theory. Strain theory attributes crime to a disparity between goals and means to achieve them. Risk factors that fall into strain theory include social status and financial status. Social learning theories describe interactions with people and situations as learning experiences through which an offender may develop criminal attitudes and ultimately exhibit corresponding behavior. Indicators of social learning theories include criminal history, social supports for crime, antisocial attitudes, and substance abuse. Psychopathological theories identify mental illness as a cause of crime, with risk factors including emotional discomfort and low self-esteem. By utilizing multiple domains from different theories, risk assessments are better able to identify numerous risk factors for a better gauge of risk level (Andrews & Bonta, 2006; Bonta, 2002).

When risk assessments incorporate theory-driven domains and static and dynamic risk factors, they are considered "third generation" risk assessments (Andrews et al., 2006). By including dynamic risk factors, 3G risk assessments allow for the detection of increased risk in the presence of a circumstance that can be changed, such as current drug use. The Level of Service Inventory-Revised (LSI-R) is the most widely studied 3G risk assessment instruments for classification of offenders (Andrews & Bonta, 2006; Bonta, 2002; Holtfreter & Cupp, 2007).

The LSI-R (Andrews & Bonta, 1998) is administered as a “semi-structured interview” by supervising officers or counselors, and is largely indicative of dynamic risk factors. Psychopathy is not a focus in this instrument; rather, factors related to social learning theory and other empirically-derived factors that are most commonly found in research to be predictive of criminal behavior are included. LSI-R domains include criminal history, companions, emotional/personal, and attitudes/orientation, which are indicative of the “Big Four” risk factors (Bonta 2002). Research has found this instrument to have high predictive validity for both general and violent recidivism, even across racial categories (Andrews & Bonta, 2006; Folsom & Atkinson, 2007, Gendreau, Goggin, & Smith, 2002; Girard & Wormith, 2004; Lowencamp, Holsinger, & Latessa 2001; Van Voorhis, 2000). However, a recent review of empirical studies (Holtfreter & Cupp, 2007) found that the LSI-R’s predictive validity for females is limited, especially when compared to males. This finding was said to be due to the fact that the LSI-R had been developed and validated using a male population (Belknap, 2007; Holtfreter & Cupp, 2007). This issue is common in risk assessment, as assessment instruments are generally created using criminological theories that were based on male criminality.

Overall, the primary criticisms of third-generation risk assessments are their failure to include a lack of “gender sensitivity” and using risk as the “dominant focus” (Brennan, Dieterich, & Ehret, 2009). Research has discussed the importance for identification of criminogenic needs and issues pertaining to responsivity. By highlighting dynamic risk factors as criminogenic needs, risk assessment can aid agencies in identifying and targeting those needs in treatment. Furthermore, not all offenders are equally capable of achieving change through a particular method of intervention. The term “responsivity” as used to describe this issue in risk assessment and treatment. Offender limitations, such as maturity, learning disability, or other deficits in aptitude should be taken into consideration in risk assessment, as these issues may restrict the effectiveness of intervention (Andrews & Bonta, 2006).

“Fourth generation” (4G) risk assessments are the most current recognized developments in risk assessment (Andrews et al., 2006, Brennan et al., 2009). At the most basic level, 4G assessments bring a consideration of offender needs and responsivity to a shared focus with risk. Resiliency factors that compromise risk, such as social supports for prosocial behavior, noncriminal peers, and adequate employment and housing, are also included. Additionally, 4G risk assessments are to be advanced enough electronically to facilitate integration between agencies to promote consistency and more complete data collection and analysis. This electronic advancement is achieved through the use of comprehensive databases and internet application for assessment systems.

Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) is a noted 4G instrument that has been validated in recent study (Brennan et al 2009), which lends support to the argument for advancements in risk assessment at the level of 4G instruments. COMPAS addresses issues of responsivity by examining risk and need as they relate to treatment. The assessment is designed to be integrated into an agency’s database system to track decision making processes and outcomes. Additionally, COMPAS was designed using separate risk factor calibrations for males and females; validation for females and males were also conducted separately to ensure gender sensitivity. COMPAS taps several theoretical sources for risk factor domains, including social learning, social control, strain, and other theories of crime.

Contemporary Accuracy Concerns

Actuarial risk assessments are not without limitations. Krauss and Lieberman (2007) point out that risk factors specific to an individual's situation may not be included in a risk assessment instrument that is designed to be used on a variety of offenders in different sets of circumstances. In other words, a standardized risk assessment inherently does not allow for individualization in the identification of risk factors.

Other limitations of some actuarial risk assessments may include a lack or limited use of dynamic risk factors and lack of generalizability. Dynamic risk factors, which may change and vary, are important to identify due to relevance to the offender's current situation and immediate impact on likelihood for recidivism. Also, risk assessments that are not generalizable are limited in that predictive accuracy may not hold for a wide population of offenders (Folsom & Atkinson, 2007; Girard & Wormith, 2004; Holsinger & Latessa, 2001; Schwalbe, Fraser, Day, & Cooley, 2006). Risk assessment instruments should be accurate in prediction of recidivism for subgroups, such as race and gender, within a population of offenders so that services are provided efficiently to the entire population. Research has commonly identified gender as an issue even when referring to the well-validated LSI-R (Folsom & Atkinson, 2007; Girard & Wormith, 2004; Holsinger & Latessa, 2001). Additionally, Schwalbe et al. (2006) found differences in accuracy of prediction of recidivism among juveniles across race/ethnicity using the North Carolina Assessment of Risk (NCAR). Because the NCAR is designed to be a brief instrument, Schwalbe et al. (2006) posit that this finding may be the result of "omitted variable bias," or the possible exclusion of risk factors that may be more or less common in different subgroups of a population. Specifically, it is noted that certain "contextual risks" such as neighborhood environment may be more common to minorities than the white population, and may be a source of omitted variable bias when unaccounted for in risk assessment.

In light of limitations, actuarial risk assessment has continued to develop to overcome these limitations and to better meet the needs of criminal justice agencies. Risk Management Systems (RMS; Modeling Solutions, LLC, 2005) has emerged as a self-proclaimed “Fifth Generation” risk assessment instrument designed to predict risk of recidivism, identify criminogenic needs and issues related to responsivity, address the need for technological advancement, and use advanced statistical modeling to aid in decision making. The statistical modeling used by RMS is the primary advancement that the instrument makes over previous assessment instruments.

Risk Management Systems

Risk Management Systems (RMS; Modeling Solutions, LLC, 2005) is a recently developed risk assessment instrument that has yet to be validated using a population external to the population on which it was created. It is currently used by United States Probation, District of Nevada to aid in the prediction of recidivism among offenders. The RMS is a 65 item instrument with items to identify both static and dynamic risk factors in order to provide a risk score for recidivism, a risk score for violence, and identification of criminogenic need areas for treatment.

The RMS was developed using exemplar-based empirical modeling (Dow, unpublished). This method consists of comparing offenders based on patterns of indicators, rather than an index score on a scale (as used by other risk assessment instruments) (Dow, Jones, & Mott, 2005, Dow & Streveler, 2006). The data used for comparison in empirical modeling is derived from cases examined with known outcomes, with "salient factors" exclusive to groups of higher or lower risk offenders. Exemplars are those cases in a "reference library" that best characterize groups of higher or lower risk. A specific offender is compared to a dynamic model that depends on the exemplars with the closest matching data patterns for calculation of risk level. This method of empirical modeling was studied with offenders from the Wisconsin Department of Corrections using the Receiver Operating Characteristic (ROC), which found an Area Under the Curve (AUC) of .94, indicating effectiveness of classification in this sample (Dow, Jones, & Mott, 2005).

In the first section of the instrument, "Assessment of Offender Needs", one scale item is dedicated to each of 11 need areas which include academic, employment, financial management, relationships, companions, emotional, alcohol, drug, mental ability, health, and sexual behavior. The last item in this section solicits the impression of the person completing the assessment regarding overall needs. The companions need relates to social supports for crime, which is identified in the "Big Four," and highlighted in social learning and control theories of crime. Academic, employment, relationships, and substance abuse factors can all be found in the "Central Eight." Academic and employment indicators are also discussed in strain theory as potential evidence for disjuncture between means and goals. The employment and relationships items indicate social controls for crime as discussed in social control theory.

The second section, "Assessment of Offender Risk," employs 11 scale items to identify static and dynamic risk factors. Included in this section are: number of address changes in the last year, percentage of time employed in the last year, alcohol usage problems, other drug problems, attitude, age at first conviction, number of prior periods of probation/parole, number of prior probation/parole revocations, number of felony convictions, convictions for juvenile adjudications, and convictions or juvenile adjudications for assaultive offense within the last five years. This section also devotes items to primary risk factors, including criminal history and antisocial attitudes, which are derived from social learning theory. Criminal history items are records of behavior that could be tied to antisocial attitudes and personality, which are aspects of learned behavior that are conducive to criminal behavior, according to social learning theory.

"Mental Health Problems" are specifically at target in the third section with 10 items that are based in psychopathological theories of crime. This section asks the assessor to indicate the presence of self-concept problems, interpersonal problems, emotional problems, mental health treatment history, destructive behavior, unusual behavior or thought disorder, learning disability/mental retardation, criminal/antisocial value system, and other mental health concerns. The final item in this section asks whether the offender will be referred to mental health services. This section has relevancy to antisocial personality and attitudes as well as issues that affect responsivity.

The fourth section, "Other," includes 32 items to capture additional information regarding a variety of domains. Items dedicated to criminal history include the number of previous misdemeanor convictions and probations, number of previous felony convictions and probations, number of times released on parole, number of prior incarcerations, reason or type of admission to supervision, and governing index offenses. Items dedicated to issues of employment and education include living arrangement, amount of time employed, months at current job, job classification, gross monthly income, job training wanted by offender, and last grade completed. Additional items covering finances include number of dependents, making support payments, payments received for worker's compensation, Social Security, VA benefits, unemployment compensation, aid for dependent children, general relief, and other payments. The remaining items inquire about primary client management classification, need for child care, veteran status, institutional security level at time of release, sex, age, admission date, and expected release date. The items in this section of the RMS also cover domains that can be tied to theory. Criminal history items again work as indicators of behavioral manifestation of antisocial attitudes and personality that develop through the learning process described in social learning theory. Items regarding finances and socioeconomic status refer back to strain theory.

Although the RMS utilizes theoretically based major and moderate risk factors, both static and dynamic, only a few indicators were dedicated to each. Multiple indicators for each risk factor are the empirically preferred method in risk assessment (Bonta, 2002). This is due to variance in definitions and the diverse nature of human behavior. For example, substance abuse can be characterized by multiple indicators, including, but not limited to, history of drug-related criminal charges, history of drug treatment, scoring on separate substance abuse assessment instruments, and offender (or other person's) perception of a problem. The absence of any of these indicators does not exclude the presence of other indicators, or the presence of this risk factor in an offender's life. For this reason, risk assessments should include multiple indicators for risk factors, especially major and moderate factors that affect prediction and/or treatment.

RMS risk scores for violence and recidivism range from 1.00 (low risk) to 2.00 (high risk), using 0.01 intervals as identifying markers. To date, the RMS does not identify standard boundaries as to which scores would differentiate high, medium, or low risk offenders for classification. According to the RMS user manual (Modeling Solutions, LLC, 2005), low scores are more likely to result in an accurate prediction that an offender will not recidivate; high scores are more likely to result in an accurate prediction that the offender will recidivate, and mid-range scores indicate that a prediction of recidivism may or may not be accurate.

Current Study

The current research is a validation study of the Risk Management Systems risk assessment instrument used by U.S. Probation, District of Nevada. The current study focuses on the recidivism and violence risk scores to explore the instrument's predictive validity. The RMS has yet to be validated for ability to predict recidivism and violence. Because this instrument is used in case management to determine treatment and supervision of offenders, the study has important implications for criminal justice agencies, officers, offenders, and the community.

The purpose of the current study is to examine the utility of the RMS for prediction of recidivism one to two years following assessment. Literature indicates that higher risk scores are correlated with higher rates of recidivism (Dow, Mott, & Jones, 2005); conversely, lower risk scores are correlated with lower rates of recidivism. Therefore, the current study hypothesizes that the RMS recidivism scores and violence scores will correlate positively with recidivism.

CHAPTER 3

METHODOLOGY

Sample

The current research is an examination of secondary data. United States Probation Office, District of Nevada implemented the use of Risk Management Systems for risk assessment in April 2007, with an entry deadline of May 2007 for the current caseload. The dataset consists of a sample of 830 USPO District of Nevada, Las Vegas office clients under supervision at the time of assessment implementation, and individuals who were assessed as new clients between April 1, 2007 and October 31, 2007. This time period was identified to allow for at least a one year follow up period for collection of recidivism data[1].

Originally, the sampling frame consisted of 1192 cases from the RMS database; 11 cases were eliminated because the offender identification numbers were simply practice cases in the RMS database, 271 were eliminated because the cases were from the Reno office and arrests could not be tracked using the local arrest data provided, 30 were eliminated because they transferred to another district during their follow up period, and 25 were eliminated because the offender was not in USPO custody during the time observed (often still in the custody of Bureau of Prisons). Five cases were eliminated because demographic data on the offender did not match the RMS database (which indicated that these may also have been practice cases). Three cases were eliminated due to death of the probationer during the follow up period. Fourteen of the cases were duplicated in the RMS database due to availability of updated information on the

[1] The follow up period for technical violations and termination status was 12 months. However, the follow up period for arrests ranged from 16 to 26 months.

offender; in these cases the first assessment date and scores were used. Arrest data were not available for three offenders, leaving 830 felony and misdemeanor offenders in the sample.

Eighty-one percent of the offenders were male, 19% were female. Fifty-three percent of the sample was White, 28% Black, and 19% other. Average age was 40.4 years, with a range of 19 to 78 and standard deviation of 11.6 years. (Table 1).

Independent Variables

The two independent variables are the RMS scores for recidivism and the RMS scores for violence. RMS scores are measured on an interval scale, and can range from 1.00 to 2.00 with 0.01 increments. USPO's RMS database provided data. A full range of RMS scores were covered in this sample, with scores ranging from 1.00 to 2.00 for both recidivism and violence scores.

Dependent Variables

USPO, District of Nevada uses SCOPE (Shared Computer Operation for Protection and Enforcement) as a method of tracking recidivism among clients. SCOPE is an internal computer system that local criminal justice agencies use to enter and retrieve arrest and court disposition data. USPO utilizes the Clark County network of SCOPE, which includes data entered by Las Vegas Metropolitan Police Department, North Las Vegas Police Department, Boulder City Police Department, Henderson Police Department, Nevada Highway Patrol, and Nevada Probation and Parole.

Table 1

Offender Demographics

Characteristics	n	%
Race		
White	438	52.8
Black	236	28.4
Other	156	18.8
Gender		
Male	673	81.1
Female	157	18.9
Age		
19-25	54	6.5
26-35	267	32.2
36-45	259	31.2
46-55	149	18.0
56 +	101	12.2
M (SD)	40.4 (11.6)	

Recidivism was conceptualized as re-arrest for any non-traffic offense, and measured as the presence or lack of re-arrest during a one year or greater follow-up period using SCOPE reports provided by USPO for the sample. Arrest data for absconders was coded as missing due to potential invalidity of local arrest data for an offender whose whereabouts are unknown. Due to variance in dates of assessments and dates of arrest reports, follow up periods range from 16 to 26 months[2].

Additionally, the study examined a dichotomous measure of any technical violation filed to the court as a measure of outcome within a 12 month follow-up period. This included a range of technical violations with varied levels of severity. The study also examined the occurrence of unsuccessful terminations from supervision as a measure of

[2] The study initially set a 12 month follow up period for all outcome variables. Due to low recidivism rates, the follow up period for arrest was extended to capture all available arrest data. Data for unsuccessful terminations and technical violations were already collected at this decision point, and therefore the follow up time was not extended for these variables.

outcome within a 12 month follow-up period. Unsuccessful terminations included revocation, absconding, and other non-revocation (yet unsuccessful) terminations.

Control Variables

Comparisons between groups were made according to age, gender and race/ethnicity to examine the predictive validity of the RMS across groups (See Table 1 for offender demographics). Age was used as a continuous variable. Gender was coded dichotomously (1=male, 0=female). Race/ethnicity codes were collapsed into White, Black, and other. USPO case files provided offender demographics.

Due to the range in follow-up periods for arrest data, time followed was controlled for when arrest was the outcome variable analyzed. This was calculated as the difference between assessment date and date that SCOPE arrest data were printed. The mean time followed was 21.20 months and standard deviation of 2.37 months.

To control for current offense type, the most serious offense at start of supervision was identified by type and ranked. These data were available in each offender's presentence report, judgment by the court, or misdemeanor information filing. Offense types were ranked in the following order: violent, sex, property, drug, other, firearm, and probation violation. This ranking was devised based on general trends in crime seriousness rankings that place crimes against persons over crimes against property, which are followed by victimless crimes (Stylianou, 2003). Although sex offenses can be considered to be violent offenses (Glover et al., 2002; Rice & Harris, 1995), a separate category was made for this study, as sex offenses are often focused on separately in research (Hall, 1995). Consistent with previous validation studies examining violent recidivism (Glover et al., 2002; Rice & Harris, 1995), violent offenses measured included threatening with a firearm, armed robbery, assaults, forcible confinement, manslaughter, and murder. Robbery without a weapon and arson were not included, and coded as property offenses instead.

The ranking order of drug, other, and firearm offenses was adopted from McCleary, O'Neil, Epperlein, Jones, and Gray (1981), and were chosen to best describe the data in the current study. The category of "probation violation" was added to the current study to capture behavior that resulted in revocation of a previous term of supervision. These offenses are not given misdemeanor or felony categories, but may involve new criminal behavior.

In the current study, property offenses were the most common current offense type (37.2%), followed by drug offenses (28.2%). Less common offenses included firearms offenses (13%), other offenses[3] (12.3%), and violent offenses (4.2). Probation violations (2.9%) and sex offenses were the least common (1.9%).

As the provision of treatment may moderate risk of recidivism during supervision, referrals to treatment were examined for the sample. This was measured dichotomously with the positive value representing any treatment referral made during the 12 month period following the assessment date. These included both new treatment referrals, and treatment referrals made prior to assessment in which the contract dates overlapped with the follow-up period. Approximately 38% of offenders were referred to treatment or under a prior treatment referral during the 12 month follow-up period.

[3] Other offenses included DUIs, obstruction of justice, false statements, immigration, and other infrequent offenses.

Analytic Procedures

Descriptive statistics were conducted first to examine the general data patterns within the independent, dependent, and control variables. Then, three steps of analysis were conducted: bivariate analysis, regression, and Receiver Operating Characteristic (ROC). The current research used correlations to make initial assessments about the relationship between RMS risk and violence scores and recidivism. Logistic regression was used to test this relationship while controlling for demographic variables, current offense type, treatment referral, and time followed. Finally, Receiver Operating Characteristic was be used to assess the predictive accuracy of RMS.

The Receiver Operating Characteristic (ROC) has been cited as an increasingly useful method of analysis for assessing the accuracy of risk prediction (Rice & Harris, 1995). ROC is used to demonstrate the ability to predict outcomes compared to the expected accuracy of an uninformed prediction (similar to the rate of chance). The ROC analytic technique also serves as a control for the base rate of recidivism in a sample population. ROC was employed to review the effectiveness of exemplar-based modeling for classification, as used by the developer of the RMS, Edward Dow, in empirical modeling research (Dow, Jones, & Mott, 2005).

CHAPTER 4

RESULTS

To examine the predictive validity of the RMS in the current study, analyses were conducted in three steps: bivariate analyses, logistic regression, and Receiver Operating Characteristic (ROC) analyses. This section first presents descriptive characteristics for independent and dependent variables to provide context for the analyses and results that follow. Correlation coefficients derived from bivariate analyses are then presented as an initial assessment of the relationship between RMS scores and outcomes. Logistic regression analyses are then presented to demonstrate whether and how these relationships are affected by control variables. Finally, Areas Under the Curve (AUCs) derived from ROC analyses are presented as the final step of analysis to assess the predictive validity of the RMS while controlling for base rate.

Sample Characteristics

The vast majority of offenders scored in the lower half (under 1.50) of possible scores for both RMS recidivism and violence scores. For example, 69.9% of the sample were designated an RMS recidivism score of 1.00, the lowest possible score. In addition, 76.8% of offenders scored under 1.50 for violence. Violence scores are somewhat more normally distributed than recidivism scores, with five of the 6 lower categories each holding over 10% of scores. The mean RMS recidivism score was 1.12 (SD=.23), while the mean RMS violence score was 1.33 (SD=.24) (See Table 2).

The majority of the sample did not recidivate during the follow up period, across all three outcome variables (arrest, unsuccessful termination, and technical violations, see Table 3). Only 17.7% of offenders in the sample were arrested during the follow-up period. Technical violations were filed for 21.2% of offenders. A mere 9.8% of offenders were terminated unsuccessfully from supervision within the year.

Table 2

RMS Score Distribution

	RMS Recidivism Score		RMS Violence Score	
Score Range	n	%	n	%
1.00	580	69.9	100	12.0
1.01-1.09	25	3.0	45	5.4
1.10-1.19	46	5.5	123	14.8
1.20-1.29	42	5.1	162	19.5
1.30-1.39	28	3.4	109	13.1
1.40-1.49	30	3.6	100	12.0
1.50-1.59	21	2.5	81	9.8
1.60-1.69	20	2.4	47	5.7
1.70-1.79	18	2.2	25	3.0
1.80-1.89	10	1.2	17	2.0
1.90-1.99	3	.4	13	1.6
2.00	7	.8	8	1.0

Table 3

Outcome Variable Distribution

Outcome Measure	n	%
Arrest		
Yes	147	17.7
No	675	81.3
Unsuccessful Termination		
Yes	81	9.8
No	749	90.2
Technical Violation		
Yes	174	21.2
No	648	78.8

Note: Arrest and technical violations were coded as missing for eight absconders as the validity of these variables may have been compromised due to unknown whereabouts of the offender.

Bivariate Analyses

Point-biserial correlation coefficients, presented in Table 4, reveal statistically significant positive correlations between RMS recidivism and violence scores and the three outcomes of arrest, unsuccessful termination from supervision, and technical violations. RMS recidivism scores are more strongly correlated with each of the outcome measures than RMS violence scores, with RMS recidivism coefficients ranging from .24 for technical violations to .33 for unsuccessful terminations.

Table 4

RMS Score and Outcome Correlations

Predictors	Arrest	Unsuccessful Termination	Technical Violation
RMS Recidivism Score	.296*	.332*	.237*
RMS Violence Score	.221*	.234*	.225*

Note: Arrest and technical violations were coded as missing for eight absconders as the validity of these variables may have been compromised due to unknown whereabouts of the offender.

**p* < .001

Area Under the Curve

In the next stage of analysis for the current study, Receiver Operating Characteristic (ROC) analyses were utilized to assess the predictive validity of the RMS. Rice & Harris (1995) have stated that ROC analysis is a preferred method for analyzing predictive validity, as this method controls for base rate. Controlling for base rate is important, especially when the base rate of the dependent variable is low relative to the rate of chance. Without controlling for base rate, an instrument could be validated by predicting recidivism would not occur due to the high probability such a prediction would be true.

Area Under the Curve (AUC) is the product of ROC analysis most commonly used to describe findings (Rice & Harris, 1995). With a value of .50 representing the rate of chance, values ranging .51 to .99 indicate the degree to which a prediction is accurate. These results can also be demonstrated in the form of a plotted graph, in which a diagonal line represents the rate of chance, and curve drawn relative to the plotted points demonstrates predictive accuracy. AUC refers to the distance between the comparative diagonal line and the midpoint of the curve. An AUC of .71 or higher is considered to represent a strong level of predictive accuracy (Hosmer & Lemeshow, 2000).

Table 5 displays the Area Under the Curve (AUC) statistics that resulted from ROC analyses. RMS recidivism scores were found to be most predictive of unsuccessful termination (AUC=.72), followed by arrest (AUC=.67) and technical violations (AUC=.64). RMS violence scores were also found to be most predictive of unsuccessful termination (AUC=.71), followed by technical violations (AUC=.65) and arrest (AUC=.64). All AUC values were statistically significant with p values of less than .001.

Table 5

Area Under the Curve: RMS Scores and Outcome

	Arrest		Unsuccessful Termination		Technical Violations	
Characteristic	AUC	95% CI	AUC	95% CI	AUC	95% CI
RMS Recidivism Score	.672*	.620-.725	.719*	.651-.787	.640*	.591-.689
RMS Violence Score	.642*	.590-.695	.708*	.646-.769	.649*	.602-.695

Note: Arrest and technical violations were coded as missing for eight absconders as the validity of these variables may have been compromised due to unknown whereabouts of the offender.

*p < .001

Multivariate Logistic Regression

Although significant correlations exist between RMS scores and outcome measures, other factors associated with recidivism (e.g. age, race, nature of offense) must be controlled for. To take these factors into account, multivariate logistic regression analyses were performed for both RMS recidivism and violence scores for each outcome measure (arrest, unsuccessful termination, and technical violations). Additionally, two models were constructed for each set of independent and dependent variables to demonstrate differential impacts between a model controlling for demographics and time followed, and a model that also includes current offense type and treatment referral. As discussed below, all second models produced stronger Chi-square values and Nagelkerke R^2 values.

RMS Scores and Arrest

Table 6 presents findings of logistic regression analyses testing the association between RMS recidivism scores and arrest while controlling for demographics, time followed, current offense type, and treatment referrals during the follow-up period. These findings show that RMS recidivism scores remain significantly correlated with arrest, even when controlling for these other variables. This suggests that those with higher scores are more likely to be arrested than those with lower scores. In fact, the occurrence those scoring highest at 2.00 were 8.1 times more likely to be arrested than those scoring lowest at 1.00.

The first model in this table controls for demographics and time followed only, while the second model adds control variables for current offense and treatment referral. Both models show that in addition to RMS recidivism scores, age, race, and gender are significantly associated with arrest. Specifically, those who are younger, male, or black were more likely to recidivate. By adding current offense and treatment referral, the model was improved, bringing the Chi-square value from 121.25 to 129.97. Both Chi-square values were statistically significant. The second model reveals that treatment referral was also significantly associated with arrest, however, not in the expected direction. Treatment referral was positively associated with arrest, and offenders who were referred to treatment were nearly twice as likely to be arrested.

Table 7 presents findings of logistic regression analyses testing the association between RMS violence scores and arrest while controlling for demographics, time followed, current offense type, and treatment referrals during the follow-up period. These findings show that RMS violence scores also remain significantly correlated with arrest when controlling for other factors, suggesting that those with higher scores are more likely to be arrested than those with lower scores. However, RMS violence scores are found here to be less predictive than RMS recidivism scores, as offenders receiving the high violence scores (2.00) are only four times more likely to recidivate than those scoring low (1.00).

These models also show that in addition to RMS violence scores, age, race, and gender are significantly associated with arrest. Those who are younger, male, or black were more likely to recidivate. By adding current offense and treatment referral, the model was improved, bringing the Chi-square value from 99.07 to 114.87 (both statistically significant). The second model reveals that treatment referral was again positively associated with arrest.

RMS Scores and Unsuccessful Termination

Table 8 presents the findings of logistic regression testing the relationship between RMS recidivism scores and unsuccessful termination from supervision while controlling for demographics, current offense, and treatment referral. These findings show that RMS recidivism scores are also associated with unsuccessful termination from supervision after controlling for other factors. Age and race play a statistically significant part in these models as well. Younger probationers were more likely to be terminated unsuccessfully. Negative association between other race and unsuccessful termination shows that those whose predominant race was not White or Black were less likely to be terminated unsuccessfully.

Referral to treatment is significantly associated with unsuccessful termination in this second model as well. By adding treatment referral and current offense to the logistic regression model, the Chi-square value was raised from 85.27 to 97.35. Both models were statistically significant. The second model shows that those with high RMS recidivism scores are 16.2 times more likely to be terminated unsuccessfully than those with low RMS scores.

Table 9 presents the findings of a logistic regression testing the relationship between RMS violence scores and unsuccessful termination from supervision while controlling for demographics, current offense, and treatment referral. These findings show that RMS violence scores are associated with unsuccessful termination from supervision after controlling for other variables. Age and race play a statistically significant part in these models as well. Younger probationers were more likely to be terminated unsuccessfully. Negative association between other race and unsuccessful termination shows that those whose predominant race was not White or Black were less likely to be terminated unsuccessfully.

Referral to treatment was again significantly associated with unsuccessful termination in the second model. By adding treatment referral and current offense in the second model, the Chi-square value was raised from 59.05 to 78.22; both of which were statistically significant. The second model shows that high RMS violence scores increased likelihood of unsuccessful termination 9.1 times.

RMS Scores and Technical Violations

Table 10 shows that RMS recidivism scores are also positively associated with technical violations when controlling for other variables. Age is also a significant factor in these models, with younger people being more likely to recidivate. Race was a significant factor in the first model, with a negative relationship between “other race” and technical violations. However, this relationship was not significant in the second model when current offense and treatment referral are added. Both logistic regression models are significant, with a Chi square value improving from 62.93 for the first model to 119.75. Treatment referral was positively associated with technical violations in the second model. The second model also demonstrates that those with the highest recidivism scores were 3.1 times as likely to receive a technical violation as those scoring 1.00.

Table 11 shows statistically significant positive association between RMS violence scores and technical violations when controlling for other variables. Younger people are again shown to be more likely to recidivate in these models. Treatment referral was again found to be a significant variable in the second model. Both logistic regression models are significant, with a Chi square value improving from 60.26 for the first model to 121.46 when current offense and treatment referral are added in the second model. The second model in this table shows that those with high violence scores were 3.5 times more likely to receive a technical violation, slightly higher than in the same model using RMS recidivism scores.

Table 6

Logistic Regression Model Assessing the Relationship Between RMS Recidivism Score and Arrest

	Arrest					
	Model 1			Model 2		
	B	S.E.	Exp(B)	B	S.E.	Exp(B)
RMS Recidivism Score	2.494***	.386	12.107	2.086***	.409	8.055
Age	-.062***	.011	.940	-.058***	.011	.944
Race						
Black	.744**	.220	2.105	.814***	.223	2.258
Other	-.359	.295	.698	-.397	.306	.672
Male	.727*	.306	2.069	.632*	.311	1.881
Time Followed	.000	.001	1.000	.001	.001	1.001
Current Offense	--	--	--	.038	.074	1.039
Treatment Referral	--	--	--	.637**	.215	1.891
Constant	-3.108**	1.140	.045	-3.523**	1.210	.030
Nagelkerke R^2	.225			.242		
Model χ^2	121.248***			129.969***		

Note: Arrest and technical violations were coded as missing for eight absconders as the validity of these variables may have been compromised due to unknown whereabouts of the offender.

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

Table 7

Logistic Regression Model Assessing the Relationship Between RMS Violence Score and Arrest

	Arrest					
	Model 1			Model 2		
	B	S.E.	Exp(B)	B	S.E.	Exp(B)
RMS Violence Score	1.781***	.406	5.936	1.398**	.422	4.048
Age	-.054***	.010	.947	-.051***	.011	.951
Race						
Black	.892***	.213	2.441	.951***	.218	2.589
Other	-.346	.293	.707	-.393	.304	.675
Male	.786**	.305	2.195	.643*	.310	1.902
Time Followed	.000	.001	1.000	.001	.001	1.001
Current Offense	--	--	--	.073	.071	1.075
Treatment Referral	--	--	--	.789***	.209	2.202
Constant	-2.898*	1.200	.055	-3.587**	1.281	.028
Nagelkerke R^2	.186			.216		
Model χ^2	99.068***			114.865***		

Note: Arrest and technical violations were coded as missing for eight absconders as the validity of these variables may have been compromised due to unknown whereabouts of the offender.

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

Table 8

Logistic Regression Model Assessing the Relationship Between RMS Recidivism Score and Unsuccessful Termination

	Unsuccessful Termination					
	Model 1			Model 2		
	B	S.E.	Exp(B)	B	S.E.	Exp(B)
RMS Recidivism Score	3.314***	.431	27.490	2.788***	.452	16.245
Age	-.042**	.013	.959	-.035**	.013	.965
Race						
Black	.053	.275	1.055	.175	.280	1.192
Other	-1.183*	.467	.306	-1.187*	.478	.305
Male	-.025	.350	.976	-.200	.360	.819
Current Offense	--	--	--	.183	.094	1.201
Treatment Referral	--	--	--	.808**	.275	2.243
Constant	-4.407***	.700	.012	-5.131***	.799	.006
Nagelkerke R^2	.207			.236		
Model χ^2	85.266***			97.351***		

Note: **p* < .05; ***p* < .01; ****p* < .001

Table 9

Logistic Regression Model Assessing the Relationship Between RMS Violence Score and Unsuccessful Termination

	Unsuccessful Termination					
	Model 3			Model 4		
	B	S.E.	Exp(B)	B	S.E.	Exp(B)
RMS Violence Score	2.786***	.493	16.220	2.209***	.511	9.105
Age	-.032**	.012	.969	-.025	.013	.976
Race						
Black	.286	.260	1.331	.370	.267	1.448
Other	-1.138*	.461	.321	-1.142*	.473	.319
Male	.081	.343	1.084	-.164	.354	.849
Current Offense	--	--	--	.221	.087	1.247
Treatment Referral	--	--	--	1.009***	.266	2.742
Constant	-4.911***	.873	.007	-5.644***	.951	.004
Nagelkerke R^2	.145			.192		
Model χ^2	59.050***			78.221***		

Note: **p* < .05; ***p* < .01; ****p* < .001

Table 10

Logistic Regression Model Assessing the Relationship Between RMS Recidivism Score and Technical Violations

	Technical Violation					
	Model 1			Model 2		
	B	S.E.	Exp(B)	B	S.E.	Exp(B)
RMS Recidivism Score	1.973***	.356	7.189	1.129**	.385	3.094
Age	-.032***	.009	.969	-.026**	.009	.974
Race						
Black	.255	.201	1.290	.415	.212	1.514
Other	-.526*	.267	.591	-.447	.281	.640
Male	.393	.253	1.482	.266	.264	1.304
Current Offense	--	--	--	.060	.069	1.062
Treatment Referral	--	--	--	1.427***	.198	4.166
Constant	-2.649***	.541	.071	-2.808	.616	-2.808
Nagelkerke R^2	.114			.212		
Model χ^2	62.934***			119.747***		

Note: Arrest and technical violations were coded as missing for eight absconders as the validity of these variables may have been compromised due to unknown whereabouts of the offender.

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

Table 11

Logistic Regression Model Assessing the Relationship Between RMS Violence Score and Technical Violations

	Technical Violation					
	Model 1			Model 2		
	B	S.E.	Exp(B)	B	S.E.	Exp(B)
RMS Violence Score	1.936***	.372	6.928	1.258**	.394	3.518
Age	-.026**	.009	.974	-.022*	.009	.978
Race						
Black	.355	.197	1.426	.467	.209	1.595
Other	-.507	.268	.602	-.4358	.283	.647
Male	.375	.255	1.456	.214	.266	1.238
Current Offense	--	--	--	.074	.068	1.077
Treatment Referral	--	--	--	1.452***	.195	4.272
Constant	-3.261***	.647	.038	-3.428***	.721	.032
Nagelkerke R^2	.110			.215		
Model χ^2	60.261***			121.464***		

Note: Arrest and technical violations were coded as missing for eight absconders as the validity of these variables may have been compromised due to unknown whereabouts of the offender.

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

CHAPTER 5

DISCUSSION

Previous research has shown support for the use of actuarial risk assessments for the prediction of recidivism (e.g. Grove & Meehl, 1996; Grove, Zald, Lebow, Snitz, & Nelson, 2000). Studies have validated a variety of risk assessment instruments; however, there are currently no published research studies examining the predictive validity of the RMS. The RMS is a new instrument that uses a new technique for assessing the risk level of offenders. Exemplar-based modeling is different from other commonly used risk assessments that assign scaled values to each indicator and total them up for an index score. The purpose of this study was to contribute to the literature by examining the predictive validity of RMS scores using a sample of probationers. It was hypothesized that higher RMS scores would be associated with recidivism.

Summary of Findings

The results of this study provide support for the utility of the RMS. RMS recidivism and violence scores were positively associated with three outcomes: arrest, unsuccessful termination, and technical violations. Although correlation coefficients were relatively low, ranging from .22 for violence scores and arrest to .33 for recidivism scores and unsuccessful termination, they were found to be statistically significant with a p value of less than .001. These findings are consistent with findings from studies reviewing the predictive validity of the LSI-R (Andrews, Bonta, & Wormith, 2006; Folsom & Atkinson, 2007; Holtfreter & Cupp, 2007; Lowenkamp, Holsinger, & Latessa, 2001).

Area Under the Curve (AUC) values were calculated using Receiver Operating Characteristic (ROC) analyses to determine predictive validity of RMS recidivism and violence scores for each of the three outcome measures. Results showed that both RMS score types were significantly predictive of each outcome. However, not all AUC values were high enough to be considered strong. Traditionally, an AUC value higher than .70 is considered to be the point at which predictive accuracy is notable (Hosmer & Lemeshow, 2000). Such AUC values were only found in this study for RMS recidivism (AUC=.72) and violence (AUC=.71) scores with the outcome variable being unsuccessful termination. These results as well as those found to be in the lower ranges are consistent with findings from validation studies examining the LSI-R and COMPAS instruments (Brennan et al., 2009; Folsom & Atkinson, 2007). However, these values are considerably lower than the AUC of .94 found by Dow et al. (2005) in empirical modeling research that led to the creation of the RMS. That study was conducted using the population upon which the empirical modeling reference library was created, which may explain the high AUC value.

To control for other variables associated with recidivism, two sets of logistic regression models were run for each type of RMS score and each of the three outcomes (arrest, unsuccessful termination, and technical violations). All first models controlled for offender demographics; when arrest was the outcome variable, the first models also included time followed because the follow-up period varied. In these models, age was consistently found to be negatively associated with recidivism, meaning that younger offenders were more likely to recidivate. Black offenders and males were more likely to be arrested. Offenders in the “other race” category were less likely to be unsuccessfully terminated. Existing literature tells us that risk assessments should be valid across a variety of offender groups (Folsom & Atkinson, 2007; Girard & Wormith, 2004; Holsinger & Latessa, 2001; Schwalbe, Fraser, Day, & Cooley, 2006). The logistic regression findings indicated significant positive correlations between RMS scores and outcomes remained significant even when demographic variables were controlled for. This indicates that the RMS is predictive across offender groups as recommended by prior research.

In the second set of logistic regression models, current offense type and treatment referral were added as control variables. All second models were improved (in terms of Chi-square and Nagelkerke R^2 values) over the first models by the addition of these variables. Current offense type was consistently not significant, suggesting that recidivism did not vary by offense type categories. This finding is contrary to research that points to differences in recidivism by offense type (Langan & Levin, 2002). Treatment referral, on the other hand, was consistently found to be statistically significant in all logistic regression models. However, the positive direction of this relationship was unexpected, and suggests that those who were referred to treatment were more likely to recidivate. Research indicates that treatment delivered inconsistently with risk level may actually increase risk of recidivism (Andrews & Bonta, 2006; Bonta, 2002; Bonta, Wallace-Capretta, & Rooney, 2000; Gendreau, 1996), which may explain this finding.

Overall, the second set of logistic regression models showed that those scoring highest with recidivism scores were eight times more likely to be arrested, 16 times more likely to be unsuccessfully terminated, and three times more likely to receive a technical violation than those scoring lowest when controlling for other variables. Those with the highest violence scores were four times more likely to be arrested, nine times more likely to be unsuccessfully terminated, and three and a half times as likely to receive a technical violation than those scoring lowest when controlling for other variables. The implication of these findings is that offenders scoring higher on the RMS should receive more intense supervision and treatment services.

Limitations

Several study limitations warrant discussion. A primary limitation of the sample is that the sample was taken from only one USPO district and office. Results from a geographically condensed sample may not be generalizable to other districts that employ the RMS. Also, the skewed distribution of RMS recidivism scores is also cause for concern. Nearly 70% of the sample scored 1.00 in recidivism, the lowest possible score, and nearly 77% scored in the lower half of possible violence scores. The current study used a population of offenders that included those who were assessed at the time of RMS implementation in the district of Nevada. This raises the question of whether the use of a new tool had an effect on the resulting scores. Future research may provide insight into this matter by using a sample or population of offenders who were assessed after the RMS has been implemented for some time.

Although the study utilized three outcome measures to capture recidivism, these measures may not best capture recidivism. Because all three measures rely on official records of criminal behavior, undetected criminal behavior was not captured in this study. The use of local arrest data may also limit criminal behavior captured in the study, as arrests that may have occurred outside of Clark County were not included. Arrest data was also limited in that dispositions of the arrests were not consistently available. Therefore, convictions to substantiate charges or dismissals of charges were not available to validate the criminal behavior with which offenders were charged. Given the small proportion of offenders that were arrested during the time they were followed, meaningful interpretations of the recidivistic offense types could not be made and were therefore not analyzed. Future research should include additional outcome measures. Inclusion of recidivistic offense types and arrest disposition data would diversify and strengthen findings related to prediction.

Another limitation to the study was the failure to include a measure of the intensity of service provision as a treatment control variable. A valid measure of treatment dosage was not possible to obtain for the current study. Furthermore, data regarding the level of care (i.e. individual, group, or residential treatment) and target of treatment (risk factors targeted during the course of treatment) were not consistently available for the current study.

Treatment programs that were started before observation started (RMS assessment date) or after observation ended (12 months later) were not adequately captured because the data was limited to the treatment received during the 12 month period only. Treatment in progress at the time of assessment had potential to affect risk, yet was not fully included in the data. The validity of the treatment dosage data was therefore challenged by this limitation. Data available for the 12 month period was additionally limited in that the data provided information about referral dosage, not dosage of treatment received. Knowledge of treatment received (above and beyond referral) would be a more valid measure of treatment for the purpose of analysis because treatment received (not just referred) is likely to have an impact on risk of recidivism.

Research has shown that treatment may reduce risk of recidivism when delivered appropriately with risk level, and potentially increase risk level when not delivered at a level consistent with offender risk (Andrews & Bonta, 2006; Bonta, 2002; Bonta, Gendreau, 1996; Bonta, Wallace-Capretta, & Rooney, 2000). Future research should include more in-depth controls for treatment provision. Measures of treatment dosage would provide insight into whether treatment is being provided at levels consistent with risk level, which would in turn help to explain associations between treatment provision and outcome. For example, the significant positive association between treatment referral and outcomes in the current study could have been explained by treatment being provided at inappropriate levels (Bonta, 2002; Bonta, Wallace-Capretta, & Rooney, 2000), if such data were available. Treatment data could also be used to study the utility of the RMS for tracking treatment progress.

The current study was also limited by the follow-up periods for unsuccessful terminations and technical violations, which were standardized to 12 months. If time followed had been extended for all variables, more recidivism may have been captured if the behavior occurred after the 12 month follow-up period. Additionally, many of the offenders in the sample remained on supervision during the 12 month follow-up period. This may have affected the recidivism rate in that offenders may be more likely to refrain from criminal behavior while on supervision, or that criminal behavior may be dealt with informally on the part of probation officers.

Conclusions and Implications

Offender risk assessment has evolved to meet demands for utility in offender supervision. Risk assessment instruments are expected to differentiate offenders by their risk of recidivism, so that supervising agencies can achieve efficiency in service delivery. Several instruments have emerged in an effort to advance the utility of risk assessment in supervision practices. The exemplar-based modeling approach used by the RMS is a new method of risk assessment, and the RMS instrument itself has not been featured in previous research. Despite limitations, the current study demonstrated predictive validity for the RMS as a risk assessment instrument. These findings supported the hypothesis that RMS recidivism and violence scores would be positively correlated with recidivism. Furthermore, the findings of this study support the use of an exemplar-based modeling approach in risk assessment.

Findings of this study are encouraging for agencies that are using the RMS for risk prediction with offenders. The RMS was adopted by progressive districts of U.S. Probation (including Nevada, Hawaii, and Nebraska)[4] because the instrument has been presented as an innovative method of assessment that expands upon the most recent generations of risk assessment instruments. The predictive validity found in this study points to the acceptability of the RMS as a tool to guide agencies in decision-making. Future research should expand the literature on this instrument by examining the predictive validity using other samples. Samples from multiple districts should be used to maximize generalizability to other populations. For example, the LSI-R has been

[4] Although the RMS was created using Wisconsin state probationers, Wisconsin districts of U.S. Probation have not adopted the RMS. This may be due to the difference between state level and federal level entities.

validated repeatedly in research using a variety of populations, and is therefore recognized to be a reliable and valid measure of risk.

Although the RMS demonstrated predictive validity in this study, concern may still be raised regarding the utility of the RMS for classification of offenders. Because the instrument is not presented with cut-points in the scores for categorization, agencies are left with the responsibility of making decisions about classification. There is great deal of discretion to be exercised when determining between low, medium, and high risk offenders using such a wide range of scores. Research about clinical judgment has shown that decision-makers are prone to reliance on extra-legal factors when structure is not provided (Andrews & Bonta, 2006; Bonta 2002; Krauss & Lieberman, 2007). This may result in misclassification. Therefore, measures should be taken to ensure the most appropriate use of the RMS for classification of offenders. The RMS User Manual (RMS; Modeling Solutions, LLC, 2005) does advise that the population to which the instrument will be applied should be taken into account when making decisions about distinguishing categories of offenders. Future research should examine potential cut-points in RMS score data in an effort to identify scoring groups for classification.

Because RMS assessments are conducted electronically, the central RMS database is an ever-increasing source of data. The implication of this is that recidivism data collected on offenders in this database could contribute to the expansion of the reference library used to compare and assess offender risk levels. A dynamic reference library would allow for the instrument to adjust over time and across geographic regions, which may result in increased utility. To accommodate a dynamic comparison database, agencies using the RMS should integrate the use of outcome data as a follow up practice in case management and reassessment.

Features of the RMS that make it comparable to other validated risk assessments include the use of indicators pertaining to needs and responsivity. These are important issues in risk assessment, as the identification of criminogenic needs and concerns related to responsivity are necessary precedents to appropriate treatment provision (Gendreau, 1996). Results generated from the RMS assessment include the identification of needs resulting from the items in the "Assessment of Offender Needs" section of the instrument.

The RMS provides an additional function in the identification of these needs that other risk assessments do not. This feature of the RMS can be utilized through the "What if" query function of the RMS (Modeling Solutions, LLC, 2005). A "what if" query allows supervising officers to make hypothetical changes to an assessment to see if a change in risk level will result. The purpose of this function is to allow foresight into the effects of treatment by comparing the hypothetical treatment outcome to similar cases in the database. The utility of the RMS in terms of identification of treatment needs should therefore be examined in future research. If the RMS is found to be accurate in this area in addition to its predictive utility, the instrument may then prove to be among the more advanced risk assessment instruments available.

REFERENCES

Andrews, D.A. & Bonta, J. (2006). *Psychology of criminal conduct* (4th Ed.). Cincinnati, OH: Anderson Publishing Co.

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

Belknap, J. (2007). *The invisible woman: gender, crime, and justice* (3rd Ed.). Belmont, CA: Wadsworth.

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

Bonta, J., Wallace-Capretta, S., & Rooney, J. (2000). A quasi-experimental evaluation of an intensive rehabilitation supervision program. *Criminal Justice and Behavior,* 27, 312-329.

Bureau of Justice Statistics. (2008). Probation and parole in the United States, 2007. Retrieved 1 September 2009 from the Bureau of Justice Statistics website: http://www.ojp.usdoj.gov/bjs/pandp.htm

Dolan, M., & Doyle, M. (2000). Violence risk prediction: Clinical and actuarial Measures and the role of the psychopathy checklist. *The British Journal of Psychiatry,* 177, 303-311.

Douglas, K.S., & Skeem, J.L. (2005). Violence risk assessment: Getting specific about being dynamic. *Psychology, Public Policy, and Law*, 11, 347-383.

Dow, E., Jones, C., & Mott, J. (2005). An empirical modeling approach to recidivism classification. *Criminal Justice and Behavior,* 32, 223-247.

Dow, E., & Streveler, A. (2006) Risk driven treatment assignment: Implications of similarity-based modeling. Manuscript submitted for publication.

Epperson, D.L., Ralston, C.A., Fowers, D., & DeWitt, J. (2005). Development of a sexual offense recidivism risk assessment tool—II (JSORRAT-II). In Prescott, D.D. (Eds.), *Risk assessment of youth who have sexually abused: Theory, controversy, and emerging strategies* (pp. 118-169). Oklahoma City, OK: Wood & Barnes Publishing.

Folsom, J. & Atkinson, J.L. (2007). The generalizability of the LSI-R and the CAT to the prediction of recidivism in female offenders. *Criminal Justice and Behavior,* 34, 1044-1056.

Gendreau, P. (1996). *Choosing correctional options that work: Defining the demand and evaluating the supply*. Thousand Oaks, CA: Sage Publications.

Gendreau, P., Little, T., & Goggin, C. (1996). A meta-analysis of the predictors of adult offender recidivism: What works! *Criminology*, 31, 401-433.

Gendreau, P., Goggin, C., & Smith, P. (2002). Is the PCL-R really the "unparalleled" measure of offender risk? A lesson in knowledge cumulation. *Criminal Justice and Behavior,* 29, 397-426.

Girard, L. & Wormith, J.S. (2004). The predictive validity of the Level of Service Inventory-Ontario Revision on general and violent recidivism among various offender groups. *Criminal Justice and Behavior,* 31, 150-181.

Glover, A.J., Nicholson, D.E., Hemmati, T., Bernfeld, G.A., & Quinsey, V.L. (2002). A comparison of predictors of general and violent recidivism among high-risk federal offenders. *Criminal Justice and Behavior,* 29, 235-249.

Grove, W.M., & Meehl, P.E. (1996). Comparative efficiency of informal (subjective, impressionistic) and formal (mechanical, algorithmic) prediction procedures: The clinical-statistical controversy. *Psychology, Public Policy and Law,* 2, 293-323.

Grove, W.M., Zald, D.H., Lebow, B.S., Snitz, B.E., & Nelson, C. (2000). Clinical versus mechanical prediction: A meta-analysis. *Psychological Assessment*, 12, 19-30.

Hall, G.C.N. (1995). Sexual offender recidivism revisited: A meta-analysis of recent treatment studies. *Journal of Consulting and Clinical Psychology,* 63, 802-809.

Hare, R.D. (1998). The Hare PCL-R: Some issues concerning its use and misuse. *Legal and Criminological Psychology,* 3, 99-119.

Harris, Patricia M. (1994). Client Management Classification and prediction of probation outcome. *Crime and Delinquency,* 40, 154-174.

Hemphill, J. F., & Hare, R.D. (2004). Some misconceptions about the Hare PCL-R and risk assessment: A reply to Gendreau, Goggin, and Smith. *Criminal Justice and Behavior,* 31, 203-243.

Holtfreter, K. & Cupp, R. (2007) Gender and risk assessment: The empirical status of the LSI-R for women. *Journal of Contemporary Criminal Justice,* 23, 363-382.

Hosmer, D.W., & Lemeshow, S. (2000). *Applied logistic regression*. (2nd Ed.). New York, NY: John Wiley & Sons.

Kleiman, M., Ostrom, B. J. & Cheesman, F. L. (2007). Using risk assessment to inform sentencing decisions for nonviolent offenders in Virginia. *Crime & Delinquency,* 53, 106-132.

Krauss, D., & Lieberman, J. (2007) Expert testimony on risk and future dangerousness. In Costanzo, M., Krauss, D., & Pezdek, K. (Eds.), *Expert psychological testimony for the courts* (p. 227-249). Mahwah, N.J.: Lawrence Erlbaum Associates.

Langan, P.A., & Levin, D.J. (2002). Recidivism of prisoners released in 1994. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics.

Lowencamp, C.T., Holsinger, A.M. & Latessa, E.J. (2001). Risk/need assessment, offender classification, and the role of childhood abuse. *Criminal Justice and Behavior*, 28, 543-563.

McCleary, R., O'Neil, M. J., Epperlein, T., Jones, C., & Gray, R. H. (1981). Effects of legal education and work experience on perceptions of crime seriousness. *Social Problems,* 28, 276–289.

Meithe, T.D., & Gauthier, J.F. (2008). *Simple statistics: Applications in social research*. New York, NY: Oxford University Press.

Modeling Solutions, LLC. (2005). Risk Management System: A user's manual [Computer software manual].

Monohan, J. (1981). *Predicting violent behavior*. Beverly Hills, CA: Sage.

Rice, M.E., & Harris, G.T. (1995). Violent recidivism: Assessing predictive validity. *Journal of Consulting and Clinical Psychology*, 63, 737-748.

Schwalbe, C.S., Fraser, M. W., Day, S. H. & Cooley, V. (2006). Classifying juvenile offenders according to risk of recidivism: Predictive validity, race/ethnicity, and gender. *Criminal Justice and Behavior,* 33, 305-324.

Stylianou, S. (2003). Measuring crime seriousness perceptions: What have we learned and what else do we want to know. *Journal of Criminal Justice,* 31, 37-56.

U.S. Courts. (2008). Costs of incarceration and supervised release. Retrieved 1 September 2009 from the U.S. Courts website: http://www.uscourts.gov/newsroom/2008/costs.cfm

Van Voorhis, P. (2000). An overview of offender classification systems. In Van Voorhis, P., Braswell, M. & Lester, D. (Eds.) *Correctional counseling and rehabilitation* (4th ed.) (pp.81-105). Cincinnati, OH: Anderson Publishing Co.

APPENDIX I

RISK MANAGEMENT SYSTEMS

MODELING Solutions, LLC
RMS Input form

Identification Number: (13 digit max)

Date of Birth: (ie. MM/DD/YYYY) / /

Date: (ie. MM/DD/YYYY) 12 / 8 / 2005

Mandatory Release Date: (ie. MM/DD/YYYY) / /

Part 1: Assessment of Offender Needs. Select one appropriate answer. Complete all items.

1)	**Academic/ Vocational Skills**			
	High School or above skill	Adequate skills; able to handle everyday requirements	Low skill level causing minor adjustment problems	Minimal skill level causing serious adjustment problems
2)	**Employment**			
	Satisfactory Employment for one year or longer	Secure employment; no difficulties reported; or homemaker, student, or retired	Unsatisfactory employment; or unemployed but has adequate job skills	Unemployed and virtually unemployable; needs training
3)	**Financial Management**			
	Long-standing pattern of self-sufficiency; e.g. good credit rating	No current difficulties	Situational or minor difficulties	Severe difficulties; may include garnishment, bad checks or bankruptcy
4)	**Marital/Family Relations**			
	Relationships and support exceptionally strong	Relatively stable relationships	Some disorganization or stress but potential for improvement	Major disorganization or stress

5)	**Companions**			
	Good support and influence	No adverse relationships	Associations with occasional negative results	Associations almost completely negative
6)	**Emotional Stability**			
	Exceptionally well adjusted; accepts responsibility for actions	No symptoms of emotional instability; appropriate emotional responses	Symptoms limit but do not prohibit adequate functioning; e.g. anxiety	Symptoms prohibit adequate functioning; e.g., lashes out or retreats to self
7)	**Alcohol Usage**			
	No interference with functioning	Occasional abuse; some disruption of functioning	Frequent abuse; serious disruption; needs treatment	
8)	**Other Drug Involvement**			
	No interference with functioning	Occasional substance abuse; some disruption of functioning	Frequent substance abuse; serious disruption; needs treatment	
9)	**Mental Ability**			
	Able to function independently	Some need for assistance; potential for adequate adjustment; mild retardation	Deficiencies severely limit independent functioning; moderate retardation	
10)	**Health**			
	Sound physical health; seldom ill	Physical condition or handicap interferes with functioning on a recurring basis	Serious handicap or chronic illness; needs frequent medical care	
11)	**Sexual Behavior**			
	No apparent dysfunction	Real or perceived situational or minor problems	Real or perceived chronic or severe problems	

12)	**Agent's Impression of Offender Needs**			
	☐ Minimum	☐ Low	☐ Medium	☐ Maximum

<u>Part 2: Assessment of Offender Risk.</u> Select one appropriate answer. Complete all items.

13)	**Number of Address Changes in last 12 Months (prior to incarceration for parolees)**			
	☐ None	☐ One	☐ Two or more	
14)	**Percentage of Time Employed in Last 12 Months (Prior to incarceration for parolees)**			
	☐ 60% or more	☐ 40-59%	☐ Under 40%	☐ Not Applicable
15)	**Alcohol Usage Problems (Prior to incarceration for parolees)**			
	☐ No Interference with functioning	☐ Occasional abuse; some disruption of functioning	☐ Frequent abuse; serious disruption; needs treatment	
16)	**Other Drug Problems (Prior to incarceration for parolees)**			
	☐ No Interference with functioning	☐ Occasional abuse; some disruption of functioning	☐ Frequent abuse; serious disruption; needs treatment	
17)	**Attitude**			
	☐ Motivated to change; receptive to assistance	☐ Dependent or unwilling to accept responsibility	☐ Rationalizes behavior; negative; not motivated to change	
18)	**Age at First Conviction (or Juvenile Adjudications)**			
	☐ 24 or older	☐ 20-23	☐ 19 or younger	

19)	**Number of Prior Periods of Probation/ Parole Supervision (Adult or Juvenile)**			
	☐ None	☐ One or more		
20)	**Number of Prior Probation/Parole Revocations (Adult or Juvenile)**			
	☐ None	☐ One or more		
21)	**Number of Prior Felony convictions (or Juvenile Adjudications)**			
	☐ None	☐ One	☐ Two or more	
22)	**Convictions for Juvenile Adjudications for:**			
	☐ None of the following: Burglary; Theft, Auto Theft; Robbery; Worthless Checks; or Forgery	☐ Burglary, Theft; Auto Theft; or Robbery	☐ Worthless Checks or Forgery	☐ One or more from the previous categories
23)	**Convictions or Juvenile Adjudications for Assaultive Offense within the Last Five Years**			
	☐ Yes	☐ No		

<u>Part 3: Mental Health Problems</u>. Check all of the items that are commonly characteristic of the offender's behavior:

24)	**Self-concept problems**			
	☐ Low self-esteem	☐ Grandiosity		
25)	**Interpersonal problems with:**			
	☐ Peers	☐ Authority	☐ Family	
26)	**Emotional problems:**			
	☐ Depression	☐ History of psychotic episodes	☐ Anxiety	

27)	**Mental health treatment history:**			
	☐ Inpatient	☐ Outpatient		
28)	**Destructive behavior:**			
	☐ Self	☐ Property	☐ Persons/assaultive	
29)	**Unusual behavior or Thought disorder:**			
	☐ Yes	☐ No		
30)	**Learning disability/ mental retardation:**			
	☐ Yes	☐ No		
31)	**Criminal/ antisocial value system:**			
	☐ Yes	☐ No		
32)	**Other:**			
	☐ Yes	☐ No		
33)	**Will offender be referred to Clinical Services or a Community Mental Health Agency?**			
	☐ Yes	☐ No		

Part 4: Other. Select one appropriate answer. Complete all.

34)	**Primary Client Management Classification**				
	☐ Selective Intervention	☐ Casework/control	☐ Environmental Structuring	☐ Limit Setting	☐ Not Classified
35)	**Living arrangement**				
	☐ Alone	☐ With Spouse	☐ With Parent(s)	☐ With Child(ren)	
	☐ With Sibling	☐ With Friend(s)	☐ Other	☐ Not Reported	

36)	**Number of Dependents (Enter 99 if not reported)**				
	☐				
37)	**Making Support Payments**				
	☐ Yes	☐ No	☐ Not Reported		
38)	**Need Child Care**				
	☐ Yes	☐ No	☐ Not Reported		
39)	**Veteran**				
	☐ Not a Veteran	☐ Yes, Honorable Discharge	☐ Yes, Other than Honorable Discharge	☐ Not Reported	
40)	**Amount of time employed**				
	☐ Unemployed, not looking	☐ Unemployed and looking	☐ Full-time (35-40hrs/wk)	☐ Full-time, seasonal	☐ Part-time, (20-34 hrs/wk)
	☐ Part-time (less than 20 hrs/wk)	☐ Student	☐ Homemaker	☐ Not Applicable	☐ Not Reported
41)	**Months at current job (Enter 999 if Not Reported)**				
	☐				
42)	**Job Classification**				
	☐ Professional, Technical, or Managerial	☐ Clerical, Sales, or Service	☐ Farming	☐ Skilled Trade	☐ Semi-skilled Labor
	☐ Unskilled Labor	☐ Other	☐ Not Reported		
43)	**Current Gross Monthly Income (Wages only)**				
	☐ None	☐ $1-$199	☐ $200-$399	☐ $400-$599	☐ $600-$799
	☐ $800-$899	☐ $1000 or more	☐ Not Reported		
44)	**Job Training wanted by offender**				
	☐ Yes	☐ No	☐ Not Reported		

45)	**Last Grade Completed**					
	☐ None	☐ [ ] 1-12 specify ☐ High School Graduate	☐ Some College	☐ College Graduate		
	☐ Some Graduate work	☐ Graduate Degree	☐ Ungraded	☐ Special Education	☐ GED or HED	
	☐ Technical or Vocational School	☐ Not Reported				
46)	**Number of Prior Misdemeanor Convictions (Adult Only) (Enter 99 if not reported)**					
	[ ]					
47)	**Number of Previous Misdemeanor Probations (Adult Only) (Enter 99 if not reported)**					
	[ ]					
48)	**Number of Previous Felony Probations (Adult Only) (Enter 99 if not reported)**					
	[ ]					
49)	**Number of times previously released on Parole (Adult Only) (Enter 99 if not reported)**					
	[ ]					
50)	**Number of Prior Incarcerations for one year or longer in a Federal or State Institution (Adult Only) (Enter 99 if not reported)**					
	[ ]					
51)	**Payments received: Disabled Aid/Worker's Compensation**					
	☐ Yes	☐ No	☐ Not Reported			
52)	**Payments received: Social Security (SSI)**					
	☐ Yes	☐ No	☐ Not Reported			

53)	**Payments received: VA Benefits)**				
	Yes	No	Not Reported		
54)	**Payments received: Unemployment Compensation**				
	Yes	No	Not Reported		
55)	**Payments received: Aid for Dependent Children**				
	Yes	No	Not Reported		
56)	**Payments received: General Relief**				
	Yes	No	Not Reported		
57)	**Payments received: Other**				
	Yes	No	Not Reported		
58)	**Type of admission**				
	Pending Mandatory Release Revocation Hearing	Pending Parole Revocation Hearing	Pending Probation Revocation Hearing	Alternative to Mandatory Revocation	Alternative to Parole Revocation
	Alternative to Probation Revocation	New Sentence, Mandatory Release Violator	New Sentence, Not a Violator	New Sentence, Parole Violator	New Sentence, Probation Violator
	No New Sentence, Early Release Violator	No New Sentence, Mandatory Release Violator	No New Sentence, Parole Violator	No New Sentence, Probation Violator	Returned without a new violation
	Temporary Probation or Parole Placement	Erroneous Admission			
59)	**Governing index offense #1 (write description)**				
	None				
60)	**Governing index offense #2 (write description)**				
	None				

61)	**Institutional Security Level at time of release**
	☐ Maximum ☐ Medium ☐ Medium-Out ☐ Minimum-CRC ☐ Minimum
	☐ Unclassified
62)	**Sex**
	☐ Male ☐ Female
63)	**Age**
64)	**Admission Date for current incarceration (e.g. 02/22/2000 -- MM/DD/YYYY)**
	/ /
65)	**Actual or Expected release Date for current incarceration (e.g. 03/24/2020 -- MM/DD/YYYY)**
	/ /

Submit

APPENDIX 2

DISTRIBUTION OF ALL VARIABLES

Type of Variable	Variable	n	%
Independent			
	RMS Recidivism Score		
	1.00	580	69.9
	1.01-1.09	25	3.0
	1.10-1.19	46	5.5
	1.20-1.29	42	5.1
	1.30-1.39	28	3.4
	1.40-1.49	30	3.6
	1.50-1.59	21	2.5
	1.60-1.69	20	2.4
	1.70-1.79	18	2.2
	1.80-1.89	10	1.2
	1.90-1.99	3	.4
	2.00	7	.8
	M (SD)	1.12 (.226)	
	RMS Violence Score		
	1.00	100	12.0
	1.01-1.09	45	5.4
	1.10-1.19	123	14.8
	1.20-1.29	162	19.5
	1.30-1.39	109	13.1
	1.40-1.49	100	12.0
	1.50-1.59	81	9.8
	1.60-1.69	47	5.7
	1.70-1.79	25	3.0
	1.80-1.89	17	2.0
	1.90-1.99	13	1.6
	2.00	8	1.0
	M (SD)	1.33 (.236)	
Dependent			
	Arrest		
	Yes	147	17.7
	No	675	81.3
	Unsuccessful Termination		
	Yes	81	9.8
	No	749	90.2

Dependent cont.			
	Technical Violation		
	Yes	174	78.8
	No	648	21.2
Control			
	Race		
	White	438	52.8
	Black	236	28.4
	Other	156	18.8
	Gender		
	Male	673	81.1
	Female	157	18.9
	Age		
	19-25	54	6.5
	26-35	267	32.2
	36-45	259	31.2
	46-55	149	18.0
	56+	101	12.2
	M (SD)	40.4 (11.6)	
	Current Offense		
	Violent	35	4.2
	Sex	16	1.9
	Property	309	37.2
	Drug	234	28.2
	Other	102	12.3
	Firearm	108	13.0
	Probation Violation	24	2.9
	Treatment Referral		
	Yes	318	38.4
	No	510	61.4
	Time Followed (in months)		
	16-18	164	20.0
	19-21	104	12.7
	22-24	542	65.9
	25-26	12	1.5
	M (SD)	21.20 (2.37)	

Not Used in Study			
	RPI Score		
	0-2	342	41.8
	3-5	265	32.4
	6-9	212	25.9
	M (SD)	3.65 (2.591)	
	Level of Offense(s) for Current Convictions		
	Felony only	725	87.7
	Misdemeanor only	66	8.0
	Felony and Misdemeanor	4	.5
	Probation Violation	32	3.9
	Arrest History		
	Violent Offenses	184	23.2
	Property Offenses	291	36.6
	Drug Offenses	227	28.6
	Other Offenses	363	45.9
	Juvenile Offenses	68	8.6
	Conviction History		
	Violent Offenses	191	24.1
	Property Offenses	315	39.6
	Drug Offenses	284	35.8
	Other Offenses	432	54.4
	Juvenile Adjudications	135	17.1
	Type of Treatment		
	Substance Abuse	60	7.3
	Mental Health	42	5.1
	Co-occurring Disorders	78	9.4
	Cognitive Behavioral Therapy	165	19.9
	Other	43	5.2
	Supervision Status 12 Months Post-assessment		
	Active	592	71.3
	Successfully Completed	140	16.9
	Terminated Early	17	2.0
	Revoked	71	8.6
	Absconded/Inactive	8	1.0
	Unsuccessfully Terminated- Not Revoked	2	.2

VITA

Graduate College
University of Nevada, Las Vegas

Bridget Kelly

Degrees:

Bachelor of Arts, Criminal Justice, 2007
University of Nevada, Las Vegas

Presentations:

Presenter, American Society of Criminology Annual Conference, 2008
Presenter, Western and Pacific Criminal Justice Educators Annual Conference, 2008

Publications:

Lu, H., & Kelly, B. (2008). Courts and sentencing research on contemporary China. Crime, Law, and Social Change, 50, 229-243.

Thesis Title: A Validation Study of Risk Management Systems

Thesis Committee:

Chairperson, Joel D. Lieberman, Ph.D.
Committee Member, Dr. Deborah K. Shaffer, Ph.D.
Committee Member, Dr. Hong Lu, Ph.D.
Graduate Faculty Representative, Stacey Hardy-Desmond, Ph.D., J.D.