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Recidivism, gender, and race: An analysis of the Los Angeles County Probation Department's Risk and Needs Assessment Instruments

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Dedication

This work is dedicated to my wife, Susan M. K. Howard. Without her love and support through this process I would not have been as successful as I have been. She encouraged me when I was doubtful and pushed me to improve my work.

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Abstract

This study assesses the predictive validity of an adult risk need assessment, the Los Angeles Probation Department's Risk and Needs Assessment Instruments, on 793 clients using several logistic regression models. Models were generated to look for a relationship between risk score and recidivism. This relationship is further explored across gender and race. There are two separate risk assessment instruments used in this study and the sample is separated into two separate groups. The first risk assessment instrument was based on static risk factors such as history of drug or alcohol use, age of first conviction, and conviction history. This assessment was applied to the sample group labeled investigation. The second risk assessment tool incorporated dynamic risk factors such as employment status, education, and peer group. This assessment was applied to the sample group labeled supervision. The results of the study showed that the risk scores calculated in the investigation sample had no significant relationship with recidivism in general or across race or gender. The risk scores calculated in the supervision sample had a significant relationship with recidivism. However, when examined by gender there was no relationship between risk score and recidivism for the female sample. When examined by race there was not a significant relationship between risk score and recidivism in any racial category. Suggestions for implications in practice and future research are also reviewed.

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Chapter 1: Introduction

The criminal justice system seeks to reduce recidivism, which is the rate at which offenders return to prison after they are released. High recidivism rates are one of the challenges facing the American criminal justice system. The Bureau of Justice (Alper, Durose, & Markman, 2018) reported that 83% of state prisoners released in 2005 were rearrested within the following nine years after their release. Recidivism impacts the American economic system and the livelihood of urban communities (Clear, 2007; Clear & Frost, 2014; Petersilia, 2003). According to the National Reentry Resource Center (2019), at least 95% of all offenders incarcerated in state prisons will return to the community. As such, the majority of the offender population will become returning citizens, disproportionately returning to communities with low incomes, high crime rates, and a lack of available resources (Clear, 2007; Clear & Frost, 2014; Petersilia, 2003).

The cost of the correctional system is an enormous burden on the American government. In 2006, more than $68 billion was spent on corrections in the United States (Clear & Frost, 2014). In Michigan alone, the Department of Corrections had a budget of just under $2 billion (Risco, 2015). One challenge for the criminal justice system is to lower the cost of corrections without compromising the successful rehabilitation of the returning citizen. The criminal justice system must consider how successful rehabilitation is defined and what aspects go into cultivating an environment in which this is possible. There are many approaches to reducing the likelihood of recidivism. Departments have used risk assessments in an attempt to reduce costs and best manage offenders (Zhang, Roberts, & Farabee, 2011). Assessments such as the Static-99 and STABLE-2007 are used to evaluate those who commit sexual-based crimes (Boccaccini, Murie, & Hawes, 2010; Tamatea, 2014), while substance abuse assessments are used to refer individuals to an appropriate level of counseling (Bourgon, Bonta, Rugge, Scott, & Yessine, 2010). Each of these risk assessments represent tools used in the field of corrections aimed at reducing recidivism.

Both prisons and community supervision have several tools used to control the offender population. Risk assessment tools are beneficial in classification for prison management and for identifying an individual's needs in efforts to reduce the risk for recidivism (Walsh & Cwick, 2018). Modern risk assessments are used to identify offender needs such as substance abuse treatment, vocational training, or educational deficits (Brennan, Dietrich, & Ehret, 2009). Assessments are also used to classify levels of supervision, determine what security level prison to classify an offender or how often the offender must report to an agent, and to predict the probability of future violent and nonviolent offenses (Brennan et al., 2009; Dieterich, Jackson, Mendoza, & Brennan, 2018).

Assessment tools are being used more and more in the field of criminal justice (Fass, Heilbrun, Dematteo, & Fretz, 2008; Brennan et al., 2009). In part because over the past several decades criminal justice policies have increased incarceration and community supervision in the name of public safety and security. This has led to an increased need for risk assessment tools (Clear, 2007; Clear & Frost, 2014; Petersilia, 2003). In addition, sentencing policies associated with the War on Crime and the War on Drugs political movements have increased supervision, intensive therapy programs, and a list of requirements that an offender must adhere to in order to "successfully" discharge from supervision (Clear, 2007; Clear & Frost, 2014). These policies also increased the offender population and the need for accurate risk assessment tools (Clear, 2007; Clear & Frost, 2014; Petersilia, 2003). Like the prison population, rates of community supervision have also increased dramatically, in part, due to prison overcrowding. This is especially the case when considering how the criminal justice system will manage individuals that are deemed a risk to the public (Zhang et al., 2011).

Modern risk assessments are grounded in criminological theory (Andrews & Bonta, 2006; Andrews, Bonta & Wormith, 2006; Brennan et al., 2009). To predict recidivism and assist in managing offenders in the community or prison, a combination of information is gathered about the offender's history, peer group, criminal history, substance use, and other pertinent information that has been theorized to impact future offending behavior. This information is evaluated and the offender is categorized into categories of risk, ranging from behavior or vocational risks to the chances of reoffending (Bourgon et al., 2010; Brennan et al., 2009; Turner & Fain, 2003).

In order to determine what varying levels of supervision or therapeutic programing offenders need, the criminal justice system relies on risk assessments that are generally administered by contracted mental health professionals or trained correctional staff to an offender when they are introduced in to the criminal justice system (Boccaccini et al., 2010; Turner & Fain, 2003). Assessments can provide starting points in the attempt to rehabilitate an offender. When an offender receives a high risk assessment, he or she is placed into high supervision groups and/or intensive therapy groups. These types of programs are labor intensive, as well as costly. Those who are inappropriately identified as high risk offenders will become over-treated and over-supervised, which potentially increases the risk for recidivism and deviant behavior (Bourgon et al., 2010; Dieterich et al., 2018).

Currently, there is a lack of available literature and data on modern risk assessment tools, although their use continues to increase. Risk assessments such as COMPAS are in need of empirical analysis in order to assess their accuracy and potentially increase their effectiveness, while assessments such as the LSR-I have been tested repeatedly and have been shown to have some predictive validity (Andrews & Bonta, 2006; Fass et al., 2008; Gendreau, Goggin, & Smith, 2002). Skeptics have suggested that COMPAS and other modes of risk assessments are overly complex and take too much time, while simple assessments are shown to be just as effective (Farabee, Zhang, & Yang, 2011). Still, other skeptics have shown that risk assessments are no more accurate in predicting recidivism than a lay person with no formal training who is provided with an offender's criminal history (Dressel & Farid, 2018).

This study assesses the validity of The Los Angeles County Probation Risk and Needs Assessment tools to predict offender recidivism. A more specific goal of the study is to assess accuracy of these tools across gender and race in predicting recidivism. This will be done through an analysis of data. Previous studies have used Cox proportional hazard models, Pearson product-moment correlation, or the receiver operating characteristics curve to assess the accuracy of risk assessment tools (Brennan et al., 2009; Zhang et al., 2011). Other studies have utilized a logistic regression model when assessing predictive validity in both juvenile and adult risk assessment instruments (Frick, 2017; Turner & Fain, 2003). In the present study, logistic regression will be used in evaluating the predictive validity of risk assessments.

Chapter 2: Literature Review

Theory of Risk Assessments

Risk assessments work on theoretical principles and assumptions. Among many other theories, anomie/strain, social bond, and social learning theories all support the use of modern risk assessments. A brief overview of these theories and the ways in which they are incorporated into modern risk assessments is beneficial for this study.

Strain theory posits that because of pressure from social structures some individuals become involved in deviant behavior. Strain theory assumes that human beings are moral and deviance is a product of outside forces. It seeks to answer the question: Why does a person commit crime, deviancy, or delinquency?

Merton (1938) says that deviance occurs when legitimate avenues of achieving goals defined by society are blocked by a lack of access. He identifies socially defined and accepted goals as things like owning a home or starting a family. Culturally appropriate ways to achieve these goals include obtaining stable employment or investing in one's education. Merton (1938) outlines five possible outcomes for the presence and/or absence of culturally approved goals and institutionalized means. The first is conformity, which is the acceptance of culture goals and institutionalized means by individuals in society. The second is innovation, which is the acceptance of culture goals, but the rejection of institutionalized means of obtaining those goals. The third is ritualism, the absence of culturally approved goals paired with the acceptance of institutionalized means. The fourth is retreatism, the absence of both culturally approved goals and institutionalized means. Lastly, the fifth is rebellion, which occurs when both culturally approved goals and institutionalized means have been rejected and a new set of goals and means have been substituted.

Strain theory assumes that those who are of lower social status and have limited means are more likely to participate in deviant behavior because of the disjuncture between the means they have available and the pressure of achieving economic success. Those of lower social status are more likely to become innovators and engage in criminal behavior in order to obtain culturally approved goals of wealth and status. Frustration occurs and innovation to find other means of attaining the institutionalized goal is sought. These means are often labeled as antisocial by society and thus deviancy is born (Andrews and Bonta, 2006; Bernard, Snipes, & Gerould, 2010; Cullen, Agnew & Wilcox, 2014; Merton, 1938).

Robert Agnew (1992) applied the macro principles presented by Merton to the micro level and identified three types of strain that would produce deviant behavior. These types of strain were failure to achieve positively valued goals, removal of positively valued stimuli, and confrontation with negative stimuli. When discussing the failure to achieve positively valued goals, Agnew also includes immediate goals and individual inability to achieve a goal because of the lack ability or skill. For example, having an immediate goal of purchasing vehicle. If an individual does not have the money to purchase a vehicle, they may attempt to meet this goal through stealing an automobile. Agnew also incorporates the idea that the gap between expectation and reality of goal achievement may result in anger or resentment in an individual. This anger or resentment may cause an individual to become involved in deviant behavior. For example, an individual may become angry when their ability to legally obtain a vehicle is compromised, which may lead to auto theft. The individual perception of what is fair or just is also measured in Agnew's theory (Agnew, 1992). Meaning that if an individual views their inability to legally obtain a vehicle as unfair when compared to an individual who has the means to purchase a vehicle, he or she may participate in deviancy.

Agnew (1992) states that an individual may participate in deviancy if a positively valued stimuli is removed resulting in strain. For instance, the death of a loved one or loss of stable housing may lead to an individual becoming involved in deviant behavior because of the loss of structure or stability provided by that individual or housing. The third source of strain discussed by Agnew (1992) is confrontation with negative stimuli. This stress or strain is described as stressful negative experiences such as abuse or neglect from a parental figure or negative experiences with those in positions of authority. A youth would not be able to avoid these sources of strain and may become involved in deviancy as a way to cope if all legitimate means of coping are unavailable.

Risk assessments incorporate this theory through questions assessing an individual's legitimate means of obtaining goals such as employment history or education level (Brennan et al., 2009). Both employment history and education level can assess how much an individual accepts cultural goals, as well as their use of institutionalized means to obtain these goals. Those who accept culturally approved means may have a steady work history and have obtained a moderate education level, such as a high school diploma. While those who reject these means may have an inconsistent work history and may have ended their education before finishing high school.

The Los Angeles County Probation Department's Risk and Needs Assessment for the supervision sample measures many components of strain theory (See Appendix B). *Attitude* is shaped by acceptance or rejection of cultural goals and institutionalized means. *School history* measures an individual's access to institutionalized means. Assessing *aptitude*, *health*, and *mental health* measures access to institutionalized means and ability to accept culturally approved goals. *Organization* and *social affiliation*, *peer groups*, and *family dynamics* measures the acceptance and/or rejection of culturally approved goals and institutionalized means. *Employment* can measure acceptance or rejection of cultural goals and institutionalized means. *Alcohol use* and *drug use* can be correlated to anomie/strain theory in that those that fall into the category of retreatism and rebellion may have higher rates of drug and alcohol use since they reject culturally approved means and/or goals.

The influence of social bond (control) theory is very clear in modern risk assessments (Andrews & Bonta, 2006; Brennan et al., 2009). The overall assumption of social bond theory is that the more prosocial bonds an individual has to the community, the less likely that person is to participate in criminal behavior. This theory assumes human beings are innately immoral. Therefore, the theory does not answer why people commit crime, but rather, why people do not commit crime. People will participate in criminal behavior if not properly controlled since bonds to society prevent an individual from giving into their natural tendencies towards law breaking.

Travis Hirschi (1969) lists four basic elements of social bond (control) theory: Attachment, commitment, involvement, and belief. An individual's attachment to society, through close bonds to conventional others, increases moral restraints and makes it less likely that he or she will participate in behavior that violates social norms or jeopardizes their attachment to society (Hirschi, 1969). Commitment refers to the notion that the more investment an individual puts into an activity such as education or success at a job, the higher the commitment level that individual has to conventional society, making them less likely to be willing to risk losing those conventional ties by engaging in criminal activity. The more involvement an individual has in society, the less time and/or resources they have to participate in deviant activities. Finally, belief in societal norms will decrease deviant behavior. Conversely, lack of these beliefs allow an individual to continue in natural deviant behavior (Hirschi, 1969).

Social bonds take several forms. Ties to social institutions such as religious organizations or educational institutions, is one common bond. Another is employment. Marriage and children are also viewed as social bonds that contribute to reducing deviant behavior. Research indicates that this is the case if an individual is active in his or her marriage and/or with his or her children (Bernard et al., 2010; Clear, 2007; Cullen et al., 2014; Hirschi, 1969; Petersilia, 2003). Negative social bonds in turn will increase criminal behaviors. Negative social bonds are those ties with delinquent peers, organizations, or activities. For instance, the COMPAS measures gang involvement, peer criminal participation, and family delinquency to assess risk of reoffending (Bernard et al., 2010; Brennan et al., 2009; Cullen et al., 2014; Hirschi, 1969).

The Los Angeles County Probation Department's Risk and Needs Assessment instrument for the supervision sample incorporates elements of social bond (control) theory. The assessment records information about employment, peer groups, recreation/hobby, organization or social affiliation, and school history. Each of these measures indicate either strong or weak social bonds dependent on the individual response. Measures of alcohol use and drug use could also be associated with social control (bond) theory in that those with weaker social bonds would be more likely to participate in the use of alcohol and drugs. The question of attitude measures social bonds (control theory) because it captures belief in prosocial or antisocial attitudes towards crime.

Social learning theory has heavily influenced risk assessments, such as the LSI-R. Social learning theory posits that criminal behavior is learned. The basic assumption of learning theories about human nature is that all people start out with a blank tablet. They neither desire to commit or desist from criminal behavior, but rather learn to engage in one behavior or another from those around them (Sutherland, 1939). Learning occurs through the interaction with peers. More specifically, interaction with close personal groups is where criminal behavior is learned.

The foundation of social learning theory is provided by Sutherland (1939) in *Principles of Criminology* where he outlines nine fundamental principles: 1) Criminal behavior is learned; 2) Criminal behavior is learned from interaction and communication with others; 3)The principal portion of learning occurs in settings of peers and close personal relationships; 4) Behavior is learned through the learning of technique of crime and motive or drive to commit the crime; 5) An excess of definitions favorable or unfavorable to crime determine one's behavior. To clarify, an individual's participation in delinquency is either increased in likelihood because of experiences, interactions, and examples that support such behavior or decreased because of experiences, interactions, and examples that do not support the behavior. An individual sells drugs because more often than not they are successful and obtain their goal. This increases the belief that they will not get caught and reinforces the behavior. An individual goes to school and gets a job because that is what their interactions, experiences, and examples support as acceptable to achieve success. 6) Delinquency occurs when the amount of favorable definitions that support illegal behavior outweighs the definitions that are favorable for legal behavior; 7) Associations with criminal behavior and lawful behavior are in flux and differential association may vary in frequency, duration, priority, and intensity (Sutherland, 1939). 8) The learning of criminal behavior is the same as learning any other behavior. 9) Criminal behavior is a response to needs and values, but it is not explained by these needs or values because there are lawful avenues to meet these needs.

Akers (1998) adds to learning theory with social learning theory. Social learning theory emphasizes that the learning process produces both deviant behavior and compliant behavior. The resulting behavior is dependent on the positive or negative reinforcement in social and non social situations. In other words, an individual will participate in crime if their criminal activity receives positive reinforcement and will not participate in crime if that behavior receives negative reinforcement (Akers, 1998). For example, an individual will continue to steal from a store if they receive praise and social benefits from their peer group and in their lives. If the individuals gains street credit from their peers and the personal gratification of obtaining desired material possessions, that individual will likely continue in that criminal behavior.

The Los Angeles County Probation Department's Risk and Needs Assessment Instrument incorporates social learning theory by measuring attitude, family dynamics, family finance, and peer groups. Individual attitudes are shaped and learned by interactions with family and peers. Family dynamics and family finance influence an individual's future behavior because it develops what an individual will define as acceptable and what is not acceptable. Similarly, measuring an individual's peer group (prosocial or antisocial) provides an understanding for what an individual will likely define as acceptable or unacceptable behavior.

History of Risk Assessments

The first generation of risk assessments was nothing more than the professional judgement of highly trained clinicians. There was no objective measure involved in this approach. Rather, the clinician stated whether or not he or she thought an individual was at risk for recidivism. These assessments were implemented by “qualified” professionals, such as psychologists or social workers capable of diagnosis. It was assumed that the professionals knew best. The professional would meet with the client and then, based on their educational knowledge, they would assess the likelihood of future criminal behavior. This method was plagued by bias, stereotyping, and subjectiveness. In the end, it was invalid at predicting recidivism (Andrews & Bonta, 2006; Brennan et al., 2009; Andrews et al., 2006; Gendreau, Little, & Goggin, 1996).

The weaknesses of the first generation risk assessments led to the development of second generation risk assessments. These assessments relied on static factors. Static factors are elements of an individual’s life that do not change over time. These factors are based on past behaviors. Actuarial methods were also introduced to predicting recidivism. The actuarial method of predicting recidivism relies on statistical algorithms to predict risk and recidivism (Zhang et al., 2011). Second generation assessments were more evidence based than the first generation assessments. For example, many relied on a simple additive point scale where offenders were scored based on past behavior and other historic static factors to predict future risk (Andrews and Bonta, 2006; Brennan et al., 2009; Andrews et al., 2006). The literature indicates that the second generation approach was superior to that of the first generation risk assessments (Andrews & Bonta, 2006). More specifically, the actuarial approach of second generation risk assessments has been found to be about 10% more accurate than clinicians’ predictions (Zhang et al., 2011).

Though improved, there were still several criticisms to the second generation risk assessments. These risk assessments did not have theoretical backgrounds. Relying on static factors meant that risk of recidivism could not change over time even if behavior changed. They were also not accurate when used to assess female populations. These assessments ignored gender differences and failed to take into account gender specific needs (Reisig, Holtfreter, & Morash, 2007; Rettinger & Andrews, 2010).

The Salient Factor Score (SFS) in the United States is an example of a second generation risk assessment tool. It measures type of offense, prior criminal history, age, prior parole failure, gender security classification, sentence length, risk interval, and drug abuse history (Andrews & Bonta, 2006; Ferguson, 2016). It lacks measures of dynamic factors such as employment status, marital status, or a defendant's social bonds (Andrews & Bonta, 2006; Ferguson, 2016). The SFS is heavily weighted towards prior offenses, incarceration in the last three years, and current age of the individual. While the SFS lacks true dynamic measures, it is reasonably valid and takes less time to administer than more complex risk assessments that incorporate dynamic factors (Ferguson, 2016). More specifically, a study by Andrews and Bonta (2006) found that there is a 73% chance that a random individual who falls into the recidivism category would have a higher score on the SFS than a randomly selected non-recidivist, indicating that it is a valid prediction method (Andrews & Bonta, 2006). In addition, the SFS takes approximately two minutes to administer versus 30 to 45 minutes for the COMPAS or LSI-R (Ferguson, 2016; Dietrich, & Ehret, 2009; Zhang et al., 2011).

The Los Angeles County Probation Department's Risk and Needs Investigation Assessment instrument used on the investigation sample is another example of a second generation risk assessment tool. However, a study by Turner and Fain (2003) found that this assessment tool was a poor predictor of most aspects of recidivism and that scores varied by race and gender (Turner & Fain, 2003). More specifically, the study found that black clients tended to score higher on eight out of the nine static factors measured in the assessment and males had higher risk scores compared to their female counterparts (Turner & Fain, 2003).

The third generation of risk assessments began to blend both static and dynamic factors to predict risk of recidivism. Also incorporated were systematic and objective measures of offender needs. These assessments were more empirically-backed and theoretically-guided (Andrews & Bonta, 2006; Brennan, Dietrich, & Ehret, 2009). For instance, the Level of Service Inventory-Revised (LSI-R) assessment, is a rigorously tested example of the third generation risk assessment. Meta analytical studies that compare risk assessments across generations show that the LSI-R (a third generation risk assessment) had a mean predictive criterion validity estimate of .36 compared to .32 for the Wisconsin Risk assessment and .30 for the SFS (both second generation risk assessments) (Andrews et al., 2006).

Despite these improvements, third generation risk assessments are criticized for having a narrow theoretical focus, lacking gender sensitivity, prioritizing offenders' risk levels, and lacking measures of offenders' strengths (Brennan et al, 2009). The assessment instrument used by the Los Angeles County Probation Department's Risk and Needs Assessment instrument for the supervision group is a third generation risk assessment tool. The Los Angeles County Probation Department's Risk and Needs Assessment instrument used to assess individuals being placed under supervision measures many static factors, such as education history, and dynamic factors, such as peer groups and social affiliations. A study by Turner and Fain (2003) found that black clients generally scored higher risk for employment issues and family issues on this assessment. Overall, the assessment did not score them at an increased risk for recidivism.

With the fourth generation of risk assessments, a bridge between assessment and case management was incorporated. These risk assessments provide a starting point for professionals to address individual criminogenic needs. They use a broader range of risk needs and incorporate an offender's strengths and resilience, as well as incorporate more theoretical explanations and influences (Andrews & Bonta, 2006; Brennan et al., 2009).

The Michigan Prisoner Reentry Initiative is an example of a reentry program that has been successful in reducing recidivism. The program can credit part of its success to the use of the COMPAS risk assessment, a fourth generation risk assessment tool (Clear & Frost, 2014). The assessment identifies an offender's areas of need, such as the need for vocational training, substance abuse treatment, or community bonds. The assessment also follows the offender through the criminal justice system, evolving as the individual's needs change (Andrews & Bonta, 2006; Andrews et al., 2006; Brennan et al., 2009). However, there are many criticisms of the COMPAS risk assessment. In an analysis of predictive validity, Dressel and Farid (2018) found the COMPAS risk assessment to be no more accurate in predicting recidivism than guesses made by individuals with little or no criminal justice expertise. Additionally, Zhang, Roberts, and Farabee (2011) found that much simpler and more cost-effective assessments were just as efficient in predicting rearrest in their study of California parolees.

Advantages of Modern Risk Assessments

Improved case management through accurately identified risk needs and treatment needs provided by modern risk assessments has led to improved success rates as measured in lowered recidivism of offenders in agencies that have implemented their use (Andrews et al., 2006). The Risk Needs Responsivity (RNR) is one successful approach to supervision in which an offender's risk is evaluated using a modern risk assessment tool. The offender's need is identified to place the individual in proper treatment. Case management then responds with treatment tailored to the individual offender (Gourgon, Binta, Rugge, Scott, & Yessine, 2010). Applying the RNR approach to case management has yielded significant improvements in offender success (Andrews, Zinger, Hoge, Bonta, Genreau & Cullen, 1990).

Limitations of Modern Risk Assessments

Skeptics from post-modernist theory and feminist theory suggest that risk assessments are inherently biased (Andrews & Bonta, 2006). Feminist theorists argue that risk assessments are created with only male centered theories in mind and ignore female specific risk needs such as past victimization (Reisig et al., 2007). Risk assessments are also criticized for failing to consider gender differences (Rettinger & Andrews, 2010). Gender differences are theorized to lead to different pathways to crime referred to as gendered pathways of crime. The concept of gendered pathways focuses on the life experiences and development of women who become involved in crime (Daly, 1998). It is commonly found that women who become involved in crime have a history of physical or sexual abuse as youths. Therefore, abuse may be a factor in future criminal behavior. When this observation is combined with Agnew's strain theory, abuse becomes another stressor in life and helps to explain future criminal behavior. This would be scored by a risk assessment in age of first arrest and criminal history. That is, it would be expected that female offenders who experienced a history of physical or sexual abuse would be more likely to have more frequent interaction with law enforcement and at a younger age if the strain caused by the abuse experienced as a youth had no prosocial opportunities to be addressed (Agnew, 1992). The literature gives the examples of prostitution, drug related offenses, and abuse related offenses as examples of gendered pathways (Reisig et al.,2006). Modern risk assessments fail to take into account the high rates of victimization that female offenders have experienced and the economic disadvantages they face. The combination of these factors lead to misclassification of female offenders (Reisig et al., 2006).

Modern risk assessments also fail to take into account differences in backgrounds that exist between races. Scholars call into question the samples that many risk assessments are validated on. There is an insufficient number of minorities in many of the samples used to properly validate if a risk assessment accurately predicts recidivism (Fass et al., 2008). Differences in backgrounds may contribute to variations in variables such as age of first arrest (Chenane, Brennan, Steiner, & Ellison, 2015; Fass et al., 2008). This expectation of differences in backgrounds leading to differences in offending would be supported by learning theories. Individuals are influenced by reinforcers from their social interactions (Akers, 1998; Sutherland). For instance, if it is common in one culture to mistrust law enforcement, then behaviors that are in conflict with law enforcement such as resisting arrest or providing false information will be positively reinforced in that social environment. This would potentially lead to increased contact with law enforcement and result in lengthier criminal histories and lower ages of first arrest. These individuals would then have increased risk scores when completing a risk assessment, while not necessarily being at a higher risk of recidivism.

The predictive traits used in many risk assessments are the same as those used to predict socioeconomic status (Andrews et al., 2006). In addition, there is a limited availability of data and research examining risk assessments (Dressel & Farid, 2018; Andrews et al., 2006). Although they include more comprehensive criteria, fourth generation risk assessments tend to be time consuming, which is challenging for an often over-burdened probation and parole staff (Farabee et al., 2011; Zhang et al., 2011).

In sum, the literature presents findings that indicate that the use of empirically supported risk assessments increases the ability to assess offender risk and address offender needs, which can reduce recidivism (Andrews et al., 2006; Andrews et al., 1990; Gourgon et al., 2010). However, much of the literature also indicates that there is limited applicability and accuracy in risk assessment use on women and minority populations (Fass et al., 2008; Rettinger & Andrews, 2010; Reisig et al., 2007). Currently, the literature on modern risk assessments is limited (Andrews et al., 2006; Dressel & Farid, 2018). Research that has been conducted offers mixed findings. For example, Brennan, Dietrich, & Ehret (2009) found that modern risk assessments, such as the COMPAS, predict recidivism equally well across gender and race (Brennan et al., 2009). Meanwhile, others have found that, for modern risk assessments, such as the COMPAS and the LSI-R, predictive validity varies across race and gender (Fass et al., 2008; Reisig et al., 2007). Furthermore, many evaluations of risk assessment tools are measured in-house and may also fall victim to the allegiance effect. This is when those who develop their own assessment instruments find extremely high predictive validity compared to those found by independent researchers (Zhang et al., 2011). To further the development of risk assessments in a direction to best serve the offender and the community, more independent evaluations of available assessments must be carried out (Zhang et al., 2011).

Current Study

This study seeks to add to the literature in a way that fills some of these gaps by assessing the Los Angeles County Probation Department's Risk and Needs Assessment instruments in their ability to predict risk for the full sample, across men and women, and the included racial categories. The main research question of this study is whether or not the Los Angeles County Probation Department's Risk and Needs Assessment instruments accurately predict recidivism. The study also examines the accuracy of these instruments across gender and race. The current literature on modern risk assessments is limited and this study seeks to add to the current body of literature. This study will provide replication of this general research question as proposed by Turner and Fain (2003), as well as add to the cumulative knowledge of these risk assessments by specifically addressing whether the assessments are able to accurately predict recidivism across gender and race. Previous work has only specified the descriptive statistics of men's and women's risk assessment scores, but has not yet estimated their accuracy (see Turner & Fain, 2003). This study will examine the predictive validity for men and for women, as well as by race.

Chapter 3: Methodology

Design

The present study uses secondary data from "The Validation of the Los Angeles County Probation Department's Risk and Needs Assessment Instruments" collected by Turner and Fain (2003) to perform a quantitative analysis of the Los Angeles County Probation Department's Risk and Needs Assessment Instruments. The main research question of this study is whether or not the Los Angeles County Probation Department's Risk and Needs Assessment Instruments significantly predict recidivism. The study also examines whether the risk assessments significantly predict recidivism across gender and race.

Research Questions

The present study will answer the following questions:

1. Do the Los Angeles County Probation Department's Risk and Needs Assessment Instruments significantly predict recidivism?

1a. Do the Los Angeles County Probation Department's Risk and Needs Assessment Instruments significantly predict recidivism for both men and women?

1b. Do the Los Angeles County Probation Department's Risk and Needs Assessment Instruments significantly predict recidivism for all included racial categories?

Hypotheses

For the purpose of this study, the following hypotheses and null hypotheses are used:

H1 the Los Angeles County Probation Department's Risk and Needs Assessment Instruments significantly predict recidivism for the full sample.

H0 the Los Angeles County Probation Department's Risk and Needs Assessment

Instruments do not significantly predict recidivism for the full sample.

H1a the Los Angeles County Probation Department's Risk and Needs Assessment Instruments significantly predict recidivism for both men and women.

H0a the Los Angeles County Probation Department's Risk and Needs Assessment Instruments do not significantly predict recidivism across gender or only significantly predict recidivism for men or for women, but not both.

H1b the Los Angeles County Probation Department's Risk and Needs Assessment Instruments significantly predict recidivism for all included racial categories.

H0b the Los Angeles County Probation Department's Risk and Needs Assessment Instruments do not significantly predict recidivism across racial categories or only significantly predict recidivism for some, but not all racial categories.

Data

The sample for this study is 793 clients. Three-hundred and ninety-five clients were provided and labeled as the investigation cases. The "investigation risk assessment" was used on this sample. These clients were a combination of clients that were on probation, pending sentencing, pre-plea, or in true summary programs. Three-hundred and ninety eight clients were provided and labeled supervision cases. The "supervision assessment" was used on this sample. These clients were a combination of clients who were on probation, pending sentencing, pre-plea, or in true summary programs. All clients were under the jurisdictions of the Los Angeles County Probation Department. The assessments were administered by probation officers at intake or already under supervision, as in the supervision group. This was an adult sample with ages ranging from 18-50. The data was collected from April 1997 through June 1999.

These secondary data sets were obtained from the Inter-university Consortium for Political and Social Research and are available to the public without restrictions. This data was stripped to ensure that all identifying information is anonymous to the present researcher. This dataset was obtained electronically in SPSS format. Secondary data is data that was collected by another researcher. There are several benefits to using secondary data. Using secondary data saves time in that it is generally easily accessible and removes the need to collect original data. It is heavily used in social science research because of the convenience that it provides and the cost effectiveness.

Los Angeles County Probation Department's Risk and Needs Assessment Instruments

There were two assessments administered in this study (See Appendix, Figure A). The first was administered to a sample of 395 clients labeled the investigation group. This is a second generation risk assessment scale in that it includes static factors in its assessment of the offender's risk. This is a nine-item instrument to measure risk. Each item is coded from "0" to a specific weighted value, with higher scores indicating risk of recidivism. The first item is *alcohol use problems* with the responses of "frequent abuse" (coded as "4"), "occasional abuse" (coded as "2"), and "no reported problem" (coded as "0"). *Drug use problems* is coded as "abuse" ("4") or "no reported abuse" ("0"). *Gang involvement* is coded as "known affiliation" ("2") or "no known affiliation" ("0"). *Age of first conviction and juvenile adjudication* was measured with the options of "16 or younger" ("4"), "17-23" ("2"), or "24 or older" ("0"). *Prior probation/parole grants* was measured with "one or more" ("2") or "none" ("0"). *Prior probation/parole revocation* provided the response of "one or more" ("4") or "none" ("0"). The assessment measured *convictions for assaultive offenses within the past five years* with the responses of “violent crimes with no weapon” (“4”), “property crimes” (“2”), and “none” (“0”). *Juvenile and adult convictions* were coded as “use of a deadly weapon” (“10”), “physical force/stalking/ possession of weapon” (“5”), and “none” (“0”). *Circumstances in current offense* were coded as “use of a deadly weapon” (“10”), “physical force/stalking/possession of weapon” (“5”), and “none” (“0”). These items are all static factors which cannot change as the offender changes. Each category is added together to produce an overall risk score. While probation officers use the score to label risk using four categories (“0 to 15,” “16 to 26,” “27 to 35,” and “36 or more”), the present study uses the more informative continuous scale of risk ranging from “0” to “44.”

The second risk assessment instrument was administered to 398 clients labeled the supervision group (see Appendix, Figure B). This is a third generation risk assessment since it incorporates both static and dynamic factors. This assessment measures risk on a13-item scale. Each item is coded from “0” to a specified weighted value, with higher scores indicating higher risk of recidivism. Items included *attitude,* coded as “defiant/uncooperative” (“2”), “resistant/ somewhat negative” (“1”), and “positive cooperative attitude” (“0”). This item includes *employment*, coded as “unemployed/not seeking” (“6”), “unemployed/seeking” (“3”), and “employed” (“0”). *Alcohol use* is coded as “chronic use” (“3”), “current use” (“2”), “prior use” (“1”), and “none” (“0”). *Illegal drug use* is coded as “current or chronic use” (“6”), “prior use” (“3”), or “none” (“0”). *Family dynamics* are coded as “repeated history of conflict” (“3”), “temporary family crisis” (“1”), and “no conflict” (“0”). The assessment takes into account f*amily finances* and codes this item as “severe difficulties” (“2”), “minor difficulties” (“1”), and “no current difficulties” (“0”). An offender’s *school history* is coded as either “no diploma/GED” (“2”), or “attending/graduated/GED” (“0”). Individual *aptitude* is coded as “severely impaired or illiterate" ("3"), "borderline functioning" ("1"), and "normal intellectual functioning" ("0"). *Mental health* is explored and coded as "chronic mentally ill" ("6"), "some emotional problems" ("3"), or "no known problems" ("0"). *Offender peer groups* are coded as "criminal influences/associations" ("6"), "negative influences/associations" ("3"), or "supportive/positive influences" ("0"). The assessment also takes into consideration *recreation and hobbies*. This is coded as "no constructive activities" ("1"), or "positive activities" ("0"). Social bonds are measured with *organization/social affiliation*. This is coded as either "no positive affiliations" ("1"), or "positive affiliations" ("0"). Finally, the assessment takes individual *physical health* into account and codes it as "serious handicap/chronic illness" ("2"), "interference with functioning" ("1"), or "sound physical health" ("0"). Each category is added together to produce an overall risk score. The range for risk scores is from the lowest risk score of "0" to "43" being the highest risk score. While practitioners use a three category risk score ("0 to 15," "16 to 25," and "26 or more"), this study uses a continuous scale in analysis to allow for more variance in the measure.

Dependent Variable

Recidivism. In the adult populations, recidivism was measured at 6, 12, and 18 month intervals. Arrest information was unavailable in this study. The adult probation system instead reported probation referrals, grants of probation, or prison commitments. Referral to probation is coded as "1." No referral is coded as "0." Grant of probation is coded as "1." No grant of probation is coded as "0." Prison commitment is coded as "1." No prison commitment is coded as "0." For this study, new referrals at 18 months was selected as the dependent variable because it included all categories measured for recidivism and therefore, is most inclusive. This measure allows for a conservative estimate of recidivism rates in the sample population.

Offender Characteristics

Gender. Gender is measured as “male” (“1”) or “female” (“0”).

Race. Race is recorded as “white” (“1”), “black” (“2”), “Hispanic” (“3”), or “other” (“4”).

Analytical Procedures

The Los Angeles County Probation Department’s Risk and Needs Assessment Instruments data in this study is analyzed using SPSS Version 25 to evaluate the accuracy of the assessments in predicting recidivism.

Since the outcome of interest (recidivism) is dichotomous, a series of logistic regression models will be used to estimate each assessment’s ability to predict recidivism. First, logistic regression models will be used to analyze the predictive accuracy of the Los Angeles County Probation Department’s Risk and Needs Assessment Instruments ability to predict recidivism. Two logistic regression models, one using the Investigation Risk Assessment tool and one using the Supervision Risk Assessment tool, will be estimated for the full sample. Other logistic regression models will be used to separately estimate the accuracy of each assessment to predict recidivism for men and for women in order to assess the accuracy of each scale to predict recidivism by gender. A third set of logistic regression models will then be estimated separately by race to determine the predictive accuracy across racial categories. For all analyses, significance will be estimated at the $p < .05$ level. Any risk assessment scale that falls below the $p < .05$ level will be determined to be a significant predictor of offender recidivism.

Upon the completion of these estimations, an equality of coefficients test was completed to measure if there were significant differences between gender and then between races. Previous studies have shown that the z-scores for the differences in coefficients, calculated using an unbiased estimate of the standard deviation of the sampling distribution, can be used to compute whether or not gendered or racial differences are significant (Paternoster, Brame, Mazerolle, & Piquero, 1998). The Clogg test (Clogg, Petkova, and Haritou, 1995) was performed in order to compare coefficients in racial and gender categories to determine if the coefficients were significantly different from each other. For example, the Clogg test will be used to compare the coefficient for females to the coefficient for males in order to determine whether these two effects are in fact statistically different from one another. The test will be repeated for comparison among each racial category for both samples. The test is represented by the following equation:

$$z = (b_1 – b_2) / \sqrt{} (SEb_1^2 + SEb_2^2).$$

Where b_1 = the coefficient for sample one, b_2 = the coefficient for sample two, SEb_1 = the standard error for sample one, and SEb_2 = the standard error for sample two.

Chapter 4: Results

Descriptives

The investigation sample had a total of 395 clients. A total of 389 clients provided race information. The descriptive information for the investigation sample is provided in Table 1.0. The youngest client was 18, while the oldest was 50, with a mean age of 31.8. The lowest risk score of this sample was 0, while the highest risk score was 40. The mean risk score was 10.83. Males made up 85% of the 395 client sample. Roughly 19% of the sample were white, 34% black, 44% Hispanic, and 4% were in the "other" race category.

Table 1

Descriptive Statistics for the Investigation Sample

	N	Minimum	Maximum	Mean	Std. Deviation
PRESENT AGE	391	18	50	31.80	9.36
INIT TOTAL SCORE	395	0	40	10.83	8.80
MALE	395	0	1	0.85	
FEMALE	395	0	1	0.15	
WHITE	389	0	1	0.19	
BLACK	389	0	1	0.34	
HISPANIC	389	0	1	0.44	
OTHER ETHNICITY	389	0	1	0.04	
Valid N (listwise)	385				

The supervision sample consisted of 398 participants. Table 2 displays the descriptive statistics for the supervision sample. The youngest participant was 18 and the oldest participant was 50, with a mean age of 29.82. The lowest risk score was 0 and the highest risk score was 43. The mean risk score was 13.03. Males made up 84% of the supervision sample. Whites made up roughly 23% of the sample. Blacks represented 27% of the sample, while Hispanics made up 45% of the sample and other races represented 5% of the sample.

Table 2					
Descriptive Statistics for the Supervision Sample					
	N	Minimum	Maximum	Mean	Std. Deviation
PRESENT AGE	397	18	50	29.82	9.04
INIT TOTAL SCORE	375	0	43	13.03	7.44
MALE	398	0	1	0.84	
FEMALE	398	0	1	0.16	
WHITE	392	0	1	0.23	
BLACK	392	0	1	0.27	
HISPANIC	392	0	1	0.45	
OTHER ETHNICITY	392	0	1	0.05	
Valid N (listwise)	370				

Bivariate Analysis

Investigation

An analysis of the bivariate correlations for the variables in the investigation sample show that there is a significant negative correlation between gender and age (r = -0.19, p< .01). Those who identify as male tend to be younger than those who identify as female. A significant positive correlation is observed between identifying as black and age at the time of the assessment (r = 0.22, p< .01). Blacks tended to be older at the time of the risk assessment. Identifying as Hispanic and age at time of the assessment is significantly and negatively correlated (r = -0.29, p < .01). Hispanics completing the risk assessment tended to be younger. There was a significant positive correlation between initial risk score and gender (r = 0.16, p < .01). Those who identified as male had higher risk scores than those who identified as female. Identifying as white and initial risk score are significantly and negatively correlated (r = -0.14, p < .01). Risk scores for white clients tended to be lower. There was a significant positive correlation between identifying as black and initial risk score variable (r = 0.31 , p < .01). Black participants had higher initial risk scores. Finally, identifying as Hispanic and the initial risk score variable yielded a significant and negative correlation (r = -0.17, p < .01). In general, Hispanic clients had lower initial risk scores. See Table 3 for Bivariate Correlations.

Table 3								
Investigation Sample Correlations								
Investigation		PRESENT AGE	INIT TOTAL SCORE	MALE (DUMMY)	WHITE (DUMMY)	BLACK (DUMMY)	HISPANIC (DUMMY)	OTHER ETHNCTYE (DUMMY)
PRESENT AGE	Pearson Correlation	1	-0.021	-.191**	.123*	.218**	-.294**	-0.028
	Sig. (2-tailed)		0.674	0.000	0.016	0.000	0.000	0.588
	N	391	391	391	385	385	385	385
INIT TOTAL SCORE	Pearson Correlation	-0.021	1	.162**	-.141**	.309**	-.167**	-0.047
	Sig. (2-tailed)	0.674		0.001	0.005	0.000	0.001	0.357
	N	391	395	395	389	389	389	389
MALE (DUMMY)	Pearson Correlation	-.191**	.162**	1	-0.057	-0.088	.141**	-0.034
	Sig. (2-tailed)	0.000	0.001		0.263	0.083	0.005	0.507
	N	391	395	395	389	389	389	389
WHITE (DUMMY)	Pearson Correlation	.123*	-.141**	-0.057	1	-.344**	-.420**	-0.092
	Sig. (2-tailed)	0.016	0.005	0.263		0.000	0.000	0.070
	N	385	389	389	389	389	389	389
BLACK (DUMMY)	Pearson Correlation	.218**	.309**	-0.088	-.344**	1	-.635**	-.139**
	Sig. (2-tailed)	0.000	0.000	0.083	0.000		0.000	0.006
	N	385	389	389	389	389	389	389
HISPANIC (DUMMY)	Pearson Correlation	-.294**	-.167**	.141**	-.420**	-.635**	1	-.170**
	Sig. (2-tailed)	0.000	0.001	0.005	0.000	0.000		0.001
	N	385	389	389	389	389	389	389
OTHER ETHNCTYE (DUMMY)	Pearson Correlation	-0.028	-0.047	-0.034	-0.092	-.139**	-.170**	1
	Sig. (2-tailed)	0.588	0.357	0.507	0.070	0.006	0.001	
	N	385	389	389	389	389	389	389
**. Correlation is significant at the 0.01 level (2-tailed).								
*. Correlation is significant at the 0.05 level (2-tailed).								

Supervision

A bivariate analysis of the supervision sample identifies a significant positive correlation between age at the time of the assessment and identifying as white (r = 0.14, p < .01). Those in this category were older on average when completing the assessment. There is also a significant negative correlation between identifying as Hispanic and the age at the time of the assessment (r = -0.147, p < .01). Hispanics were younger on average when completing the risk assessment. Further observation shows a significant positive correlation between identifying as black and the initial risk score (r = 0.10, p < .05). Black clients tended to have higher initial risk scores.

Finally, a significant negative correlation was found for those who identify as "other" race and the initial risk score variable (r = -0.12, P < .05). Risk scores tended to be lower for those identifying as "other" race. See table 4 for Bivariate Correlations.

Table 4

Supervision Sample Correlations

Supervision		PRESENT AGE	INIT TOTAL SCORE	MALE (DUMMY)	WHITE (DUMMY)	BLACK (DUMMY)	HISPANIC (DUMMY)	OTHER ETHNCTYE (DUMMY)
PRESENT AGE	Pearson Correlation	1	-0.095	-0.091	.144**	-0.002	-.147**	0.061
	Sig. (2-tailed)		0.065	0.071	0.004	0.961	0.003	0.227
	N	397	375	397	392	392	392	392
INIT TOTAL SCORE	Pearson Correlation	-0.095	1	-0.007	0.017	.104*	-0.055	-.120*
	Sig. (2-tailed)	0.065		0.889	0.738	0.045	0.294	0.021
	N	375	375	375	370	370	370	370
MALE (DUMMY)	Pearson Correlation	-0.091	-0.007	1	0.040	-.124*	0.060	0.035
	Sig. (2-tailed)	0.071	0.889		0.435	0.014	0.232	0.486
	N	397	375	398	392	392	392	392
WHITE (DUMMY)	Pearson Correlation	.144**	0.017	0.040	1	-.328**	-.495**	-.130*
	Sig. (2-tailed)	0.004	0.738	0.435		0.000	0.000	0.010
	N	392	370	392	392	392	392	392
BLACK (DUMMY)	Pearson Correlation	-0.002	.104*	-.124*	-.328**	1	-.545**	-.143**
	Sig. (2-tailed)	0.961	0.045	0.014	0.000		0.000	0.005
	N	392	370	392	392	392	392	392
HISPANIC (DUMMY)	Pearson Correlation	-.147**	-0.055	0.060	-.495**	-.545**	1	-.216**
	Sig. (2-tailed)	0.003	0.294	0.232	0.000	0.000		0.000
	N	392	370	392	392	392	392	392
OTHER ETHNCTYE (DUMMY)	Pearson Correlation	0.061	-.120*	0.035	-.130*	-.143**	-.216**	1
	Sig. (2-tailed)	0.227	0.021	0.486	0.010	0.005	0.000	
	N	392	370	392	392	392	392	392

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Regression Analysis

Investigation

In general, the risk scores produced by the assessment used in the investigation sample were not significantly correlated with new referrals within 18 months. Significance was not found at the .05. See Table 5.

Table 5

Investigation Sample: Risk Score and New Referral Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	INIT TOTAL SCORE	0.019	0.020	0.929	1	0.335	1.019
	Constant	-1.215	0.218	30.965	1	0.000	0.297

a. Variable(s) entered on step 1: INIT TOTAL SCORE.

This relationship was then examined by gender. The binary logistic regression showed that there is not a significant relationship between initial risk score and any new referral within 18 months for female offenders. See Table 6. This was found to be the same for male offenders. See Table 7.

Table 6

Investigation Sample: Female Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.084	0.066	1.597	1	0.206	1.088
	Constant	-1.329	0.557	5.691	1	0.017	0.265

a. MALE (DUMMY) = No

b. Variable(s) entered on step 1: INIT TOTAL SCORE.

Table 7

Investigation Sample: Male Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.015	0.021	0.495	1	0.482	1.015
	Constant	-1.248	0.244	26.189	1	0.000	0.287

a. MALE (DUMMY) = Yes

b. Variable(s) entered on step 1: INIT TOTAL SCORE.

When examining risk scores by race using binary logistic regression, the relationship between the risk assessment score and any new referral within 18 months is not significant for white participants. For black participants, the relationship between risk score and any new referral within 18 months is not significant. The relationship between risk score and any new referral within 18 months is also not significant for Hispanic participants. For all “other” races, the relationship between risk assessment score and new referral within 18 months is not significant. However, the sample size for "other" races is likely too small (n=14) for the analysis to be able to detect a significant relationship. See Tables 8-11.

Table 8

Investigation Sample: White Analysis

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	-0.035	0.071	0.241	1	0.624	0.966
	Constant	-0.737	0.505	2.125	1	0.145	0.479

a. combined race variable = 1.00
b. Variable(s) entered on step 1: INIT TOTAL SCORE.

Table 9

Investigation Sample: Black Analysis

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.036	0.030	1.444	1	0.229	1.037
	Constant	-1.149	0.465	6.101	1	0.014	0.317

a. combined race variable = 2.00
b. Variable(s) entered on step 1: INIT TOTAL SCORE.

Table 10

Investigation Sample: Hispanic Analysis

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	-0.003	0.033	0.006	1	0.940	0.997
	Constant	-1.184	0.308	14.758	1	0.000	0.306

a. combined race variable = 3.00
b. Variable(s) entered on step 1: INIT TOTAL SCORE.

Table 11

Investigation Sample: "Other" Race Analysis

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	-0.441	0.576	0.586	1	0.444	0.643
	Constant	-0.795	1.684	0.223	1	0.637	0.452

a. combined race variable = 4.00
b. Variable(s) entered on step 1: INIT TOTAL SCORE.

The risk assessment tool used in the investigation sample relied on static factors to estimate risk scores. This instrument failed to support earlier findings of static risk assessments in that there was no significant relationship between the calculated risk score and new referrals within 18 months. Previous studies have shown measures such as age of first arrest and prior criminal history to be reliable measures of future recidivism (Andrews and Bonta, 2006; Brennan et al., 2009; Andrews et al., 2006). It appears that the weight scale of this instrument may have been inaccurate. Less importance may have been given to reliable measures and more importance given to less reliable measures. The way in which each question was presented and weighted was vague (see appendix Figure A and B) and this could have led to subjective or inaccurate measures in some cases.

Supervision

In general, for every one point on the risk assessment scale for those in the supervision sample, there is a 5% increased chance that the individual will have a new referral within 18 months ($\beta = 0.05$, $p < .01$). See Table 12

Table 12

Supervision Sample: Risk Score and New Referral Analysis

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	INIT TOTAL SCORE	0.053	0.018	8.427	1	0.004	1.054
	Constant	-2.248	0.301	55.816	1	0.000	0.106

a. Variable(s) entered on step 1: INIT TOTAL SCORE, PRESENT AGE.

When examining the female supervision sample, this relationship is not significant. The risk score is not significantly related to any new referral at 18 months. See Table 13. For males, the relationship between risk assessment score and any new referrals within 18 months is significant ($\beta = 0.06$, $p < .01$) and shows a 6% increase in new referrals for every point added to the risk score. See Table 14.

Table 13							
Supervision Sample: Female Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.003	0.056	0.004	1	0.951	1.003
	Constant	-2.205	0.865	6.494	1	0.011	0.110
a. MALE (DUMMY) = No							
b. Variable(s) entered on step 1: INIT TOTAL SCORE.							

Table 14							
Supervision Sample: Male Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.061	0.020	9.539	1	0.002	1.063
	Constant	-2.268	0.327	48.132	1	0.000	0.103
a. MALE (DUMMY) = Yes							
b. Variable(s) entered on step 1: INIT TOTAL SCORE.							

Next, the relationships between risk assessment score and new referrals within 18 months were examined by race. For white clients, the relationship between initial score and new referrals within 18 months is not significant at the .05 level. For black clients, the relationship is also not significant. The relationship for Hispanics is also not significant. The “other” races category also fails to reach the level of significance. However, for the “other” race category this is likely due to an inadequate sample size (n = 19) and inadequate statistical power to detect a relationship. Overall, there are no significant relationships between initial risk assessment scores and new referrals within 18 months when examined by race. See Table 15-18.

Table 15							
Supervision Sample: White Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.076	0.041	3.496	1	0.062	1.079
	Constant	-2.741	0.710	14.892	1	0.000	0.064
a. combined race variables = 1.00							
b. Variable(s) entered on step 1: INIT TOTAL SCORE.							

Table 16							
Supervision Sample: Black Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.033	0.028	1.373	1	0.241	1.034
	Constant	-1.715	0.498	11.861	1	0.001	0.180
a. combined race variables = 2.00							
b. Variable(s) entered on step 1: INIT TOTAL SCORE.							

Table 17							
Supervision Sample: Hispanic Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.056	0.032	3.027	1	0.082	1.057
	Constant	-2.280	0.490	21.624	1	0.000	0.102
a. combined race variables = 3.00							
b. Variable(s) entered on step 1: INIT TOTAL SCORE.							

Table 18							
Supervision Sample: “Other” Race Analysis							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1b	INIT TOTAL SCORE	0.017	0.138	0.014	1	0.904	1.017
	Constant	-3.048	1.712	3.169	1	0.075	0.047
a. combined race variables = 4.00							
b. Variable(s) entered on step 1: INIT TOTAL SCORE.							

The risk assessment tool used in the supervision sample relied on static and dynamic factors to estimate risk scores. This instrument appears to support earlier findings of third generation risk assessments in that a significant relationship exists between the produced risk score and new referrals within 18 months. Previous studies have shown dynamic measures such as peer groups and attitude to be reliable measures of future recidivism (Andrews et al., 2006; Andrews and Bonta, 2006; Brennan et al., 2009). As in the investigation assessment, the way in which each question was presented and weighted was vague (see appendix Figure A and B) and this could have led to subjective answers in some cases, reducing the accuracy of the assessment.

Clogg Tests

After the binary logistic regression was completed for both samples, the Clogg Test was performed in order to compare coefficients across racial and gender categories to determine if the coefficients are significantly different from each other.

Investigation

Table 19			
Clogg Test for the Investigation Sample			
Variables	Equation	Z =	Z Table
Gender: Female/Male	$z = (0.084 - 0.015)/ \sqrt{(0.066^2 + 0.021^2)}$	1.0	0.8413
Race: Black/White	$z = (0.036+0.035)/ \sqrt{(0.030^2 + 0.071^2)}$	.92	0.8212
Race: Hispanic/White	$z = (-0.003+0.035)/ \sqrt{(0.033^2 + 0.071^2)}$	0.41	0.6591
Race: "Other"/White	$z = (-0.441+0.035)/ \sqrt{(0.576^2 + 0.071^2)}$	-0.7	0.2420
Race: Black/Hispanic	$z=(0.036+0.003)/ \sqrt{(0.030^2 + 0.033^2)}$	0.87	0.8078
Race: Black/"Other"	$z = (0.036+0.441)/ \sqrt{(0.030^2 + 0.576^2)}$	.83	0.7967
Race: Hispanic/"Other"	$z = (-.003+.441)/ \sqrt{(0.033^2 + 0.576^2)}$	0.76	0 .7764

The resulting z-scores in the investigation sample show that it can not be concluded that the two coefficients are in fact statistically different from one another in any of the equations. See Table 19. The resulting z-scores in the supervision sample show that none of the coefficients are statistically different from one another. See Table 20.

Supervision

Table 20			
Clogg Test for the Supervision Sample			
Variables	Equation	Z =	Z Table
Gender: Female/Male	$z = (0.003–0.061)/ \surd\ (0.056^2 + 0.020^2)$	-.98	0.1635
Race: Black/White	$z = (0.033–0.076)/ \surd\ (0.028^2 + 0.041^2)$	-.87	0.1922
Race: Hispanic/White	$z = (0.056–0.076)/ \surd\ (0.032^2 + 0.041^2)$	-.38	0.3520
Race: "Other"/White	$z = (0.017–0.076)/ \surd\ (0.138^2 + 0.041^2)$	-.41	0.3409
Race: Black/Hispanic	$z = (0.033–0.056)/ \surd\ (0.028^2 + 0.032^2)$	-0.54	0.2946
Race: Black/"Other"	$z = (0.033–0.017)/ \surd\ (0.028^2 + 0.138^2)$	.11	0.5438
Race: Hispanic/"Other"	$z = (0.056–0.017)/ \surd\ (0.032^2 + 0.138^2)$	.79	0.7852

Chapter 5: Discussion

Findings

This study was performed to assess the relationship between the Los Angeles County Probation Department's Risk Needs Assessment Instruments' scores and recidivism. This relationship was also assessed separately by gender and by race. There were two separate risk assessment tools used respectively on two separate samples. The analysis of the available data showed that the risk assessment for the investigation sample had no significant relationship between risk score and the measure of recidivism for the full sample or for the sample separated by gender or race. The risk assessment used in the supervision sample was significantly associated with the recidivism measure. However, when the analysis was run separately by gender this relationship was only significant for male participants. Among the female supervision sample, the relationship between the risk assessment score and new referral within 18 months was not significant. A Clogg test revealed that the differences in the coefficient for men and the coefficient for women is not significantly different from one another. Therefore, the sample size of females in the supervision sample (n = 62) may have impacted the ability of the analysis to detect a significant relationship. Additionally, when the data in the supervision group was analyzed and separated by racial categories, there was no significant relationship found between the risk score and measure of recidivism.

Implication of Results

In this study, it was established that for the Los Angeles County risk assessment, the risk scores were not significant for women or across races in predicting recidivism, particularly among the investigation sample. Therefore, if the risk assessment tool is the only reference for decision making, individuals may be assigned artificially high or artificially low risk scores. This indicates that users of risk assessments should always implement caution when using the resulting risk scores. The resulting scores cannot be considered to be 100% accurate. Practitioners should take into account other factors such as available biographical information and other risk measures when assigning supervision levels or placement in programing. Risk assessments are still statistically better than professional opinion or gut instinct. As such, the tools are worthwhile and have a place in the criminal justice world of supervision and case management. However, the assessments in this study and others are subject to error and these errors can result in damaging effects.

The focus of case management based on risk-needs-responsivity is to use risk scores to assess programing needs (Andrews et al., 2006). Offenders with artificially high risk scores can be mismanaged and their risk of recidivism increased. Lower risk individuals with artificially high scores can be placed into programming or contact with higher risk offenders. This has the potential to negatively impact low risk offenders. They can learn new criminal behavior, which may lead to recidivism. There is also a risk of victimization of this group of offenders. Placing them with offenders with true high risk scores puts them in situations where they may be victimized by this group (Andrews et al., 2006; Reisig et al., 2006).

Clients may be under-classified through the same risk assessment errors. Under-classified offenders may not have access to programming that they need. An under-classified offender may not get the right level of supervision, leaving them free to continue in antisocial behavior. These offenders may be placed with true low risk offenders, increasing chances of recidivism and victimization in the low risk offender group (Andrews et al., 2006; Reisig et al., 2006).

Study Limitations

There are several limitations to this study that should be discussed. First, the data set was from the 1990s, making it almost 25 years old. Since this time there have been several developments in risk assessment tools. Fourth generation risk assessments have been developed and some of the shortcomings of the assessment tools in this study have been addressed, such as gender specific questions and emphasizing empirically supported static risk assessment questions. For example, age of first arrest, prior record, gender, and age (Zhang et al., 2011).

Second, this data was previously collected for another study. While this did provide many benefits, as discussed previously, it does present some limitations. How the data was collected can be called into question since it was not collected according to the present study's objectives or with the current researcher's oversight. Therefore, how the assessments were administered by the probation officers is unknown. In addition, validity of the risk assessment may be limited. The use of an inter-rater reliability test may have increased the predictive validity of the risk assessments. The data provided also relied on mostly self-reported data to produce risk scores in the supervision sample. It has been suggested that participants are often able to figure out what answers will present them in the best light resulting in lower risk scores than an appropriate measure would assess (Farabee et al., 2014; Zhang et al., 2011). This is only as accurate as the participant is willing to be truthful. The instrument would have benefited from built in validity checks, such as questions posed several times on different formats to assess the participants answers for consistency.

For this study, the measure of risk was assessed as continuous instead of risk categories. This may limit the application of the results to practitioners who use the risk categories in case management standards. The overall variance in score may not impact the risk categories that are defined by the risk assessment.

The measure for recidivism in this case was any new referral to the Los Angeles County Probation Department within 18 months. This only measures reported crime and does not take into account any non-reported crimes or dismissed crimes committed by the sample population. It is also driven by police activity rather than offender behavior. Undocumented criminal activity would show that the measure is not indicative of new criminal behavior. In all likelihood, there were more individuals that participated in criminal behavior than reported in this study. The measure of any new referral in 18 months only records those that were reported and then were pursued by the prosecutor.

Finally, the sample used for the “other” race category in both the supervision sample and the investigation sample were much too small to produce a reliable analysis. The results of the analysis for “other” race cannot be assumed to be applicable to the general population.

Looking to the Future

The challenge of predicting human behavior will always exist for criminal justice practitioners. At best, significant relationships between behaviors, experiences, and resulting outcomes can be observed for patterns. This study further supports the need for continued research emphasizing the importance of accurate measures to develop risk assessment tools. Risk assessment tools control the flow of funds for programing and who is eligible for the programing, as well as the level of supervision for offenders. The tools used must be accurate and effective in order to provide the services needed. This study did find that the male coefficient and female coefficient in the supervision sample were not significantly different though it was found that there was not a significant relationship between risk score and new commitment within 18 months for female participants. As stated earlier, this could be due to the limited sample size provided for the females in the supervision sample. Therefore, future studies would benefit from a larger female presence in the sample of participants.

It is important to include gendered questions, as suggested by previous literature (Reisig et al., 2006; Van Voorhis, Wright, Salisbury, & Bauman, 2010). Fourth generation risk assessments have adopted this to some extent, but studies have shown that these measures would benefit from additional research (Reisig et al., 2006; Van Voorhis et al., 2010). Previous research has shown that pathways to crime differ by gender and that female pathways often include prostitution, substance abuse, and crimes that occur within the context of a cycle of victimization. These crimes involve individuals that experience victimization and at times repeat the cycle by victimizing others (Reisig et al.,2006). This should be taken into account in developing risk assessment tools. Specific gender sensitive measures would benefit from the future use of risk assessments for female populations. The risk assessment tool used in the supervision group lacked gender responsive measures, which may have contributed to the lack of predictive validity in the risk assessment score. Previous studies support the use of gender responsive measures to increase the accuracy of the risk assessment and to take into account gendered pathways of crime (Reisig et al, 2006; Van Voorhis et al., 2010).

Future studies should also consider race pathways to crime or similar concepts to improve the validity of risk assessment tools. As previously stated, there are differences in the means of risk assessment score between races. In order for such scores to be meaningful, future research would benefit from finding race-neutral questions or, similar to gendered pathways to crime, look for associations between pathways to crime and race relationships. The risk assessment tool used in the supervision sample also lacked race-responsive questions. This may be a reason why the scores produced by the assessment are not significantly related to recidivism. The mean score was the highest for participants who identify as black (14.28) and the mean risk score for participants who identified as Hispanic was the lowest (12.54). The "other" race category was the true lowest score, but is not included in this discussion because of the limited sample size and statistical accuracy. Future research should examine what accounted for these differences in scores and how can they be improved to better predict future recidivism. This finding is similar to the findings that states that black participants are often over-classified by risk assessment tools. Fourth generation risk assessment tools such as the COMPAS assessment often result in over-classifying black participants (Faas et al., 2008).

Additionally, future focus should be on the predictive variables that have been labeled "the big four" by Andrews and Bonta (2006) and include only empirically supported static factors. Andrews and Bonta (2006) identify four risk/need categories that are significantly correlated with predicting future criminal behavior: antisocial peers, antisocial cognition, past antisocial behavior, and antisocial personality patterns (Andrews and Bonta, 2006; Rettinger & Andrews, 2010). Antisocial peers include peers and associates that are active in antisocial behavior. Antisocial cognition is demonstrated in individual behavior that rationalizes criminal behavior or behavior that demonstrates cognitive behavioral issues, such as antisocial attitudes and beliefs that influence decision making. Past antisocial behavior is demonstrated in previous criminal behavior and represents the thought that past behavior best predicts future behavior. Antisocial personality patterns are represented by histories of conflict with peers and positions of power (Andrews & Bonta, 2006; Rettinger & Andrews, 2010). Practitioners should take these variables into account when creating measures and weighing categories for a risk assessment. Studies have shown that these variables have a significant relationship with recidivism. More specifically, offenders that are identified as associating with antisocial peers and having antisocial behavior, antisocial cognition, past antisocial behavior are at a higher risk for recidivism (Andrews and Bonta, 2006; Dieterich et al., 2018; Rettinger & Andrews, 2010).

To conclude, this study serves to validate the need for improved risk assessment scales, including the potential need for including both gender-responsive questions and race-responsive questions when assessing risk scores for the offender population. This could increase the accuracy of predicting future deviant behavior, as well as properly address the needs of the offender. In addition, this study serves as a reminder that risk scores should not be the only factor relied upon for case management. Both risk assessments and the experience and knowledge of a practitioner play a role in successful supervision.

Appendix

Figure - A	
Investigation Adult Risk Assessment	
Question	**Response**
Alcohol Use Problems (Prior to and including present offense)	• Frequent abuse: serious disruption: needs treatment - 4 • Occasional abuse: some disruption of functioning - 2 • No reported problem - 0
Drug Use Problems (Prior to and including present offense)	• Abuse: disruptive of functioning - 4 • No reported problems - 0
Gang Involvement (History or indicated by current offense)	• Known affiliation - 2 • No known affiliation - 0
Age at First Conviction/Juvenile Adjudication	• 16 or younger - 4 • 17 - 23 - 2 • 24 or older - 0
Prior Probation/Parole Grants: (Formal or informal probation grants)	• One or more -2 • None - 0
Prior Probation/Parole Revocations: (Adult/Juvenile)	• One or more - 4 • None - 0
Adult Conviction/Juvenile Adjudication for Assaultive Offense within past five years:	• Crimes of violence without use of weapon - 4 • Crime against property - 2 • None - 0
Adult Conviction/Juvenile Adjudication	• Use of deadly weapons - 10 • Possession of deadly weapon; use of physical force, stalking - 5 • None - 0
Circumstances present in current offense	• Use of deadly weapons - 10 • Possession of deadly weapon; use of physical force, stalking - 5 • Not applicable - 0

Figure - B		
Supervision Adult Risk Assessment		
Question	**Response - weight**	**Theory**
Attitude	• Defiant: Uncooperative - 2 • Resistant: Somewhat Negative -1 • Positive: Cooperative	Social Learning (Differential Association) Anomie/Strain
Employment	• Not employed in past six months: No efforts to seek employment - 6 • Employed in past six months: seeking employment -3 • Employed full-time/Part time -0	Social Bond (Control)
Alcohol Use	• ChronicUse - 3 • Current Use - 2 • Prior Use - 1 • None	Social Bond (Control) Anomie/Strain
Illegal Drug Use	• Current or Chronic Use - 6 • Prior Use - 3 • None - 0	Social Bond (Control) Anomie/Strain
Family Dynamics	• Repeated history of family conflict - 3 • Temporary family crisis - 1 • None - 0	Social Bond (Control) Social Learning (Differential Association) Anomie/Strain
Family Finances	• Severe difficulties - 2 • Minor difficulties - 1 • No current difficulties - 0	Social Bond (Control) Social Learning (Differential Association)
School History	• No high school diploma or equivalent - 2 • Attending school, graduated, GED or equivalent - 0	Social Bond (Control)
Aptitude	• Severely impaired functioning, Illiterate - 3 • Borderline functioning - 1 • Normal intellectual functioning - 0	Anomie/Strain

Figure - B		
Supervision Adult Risk Assessment		
Question	**Response - weight**	**Theory**
Mental Health Status	• Chronically mentally ill: hospitalized or psychosis in past year - 6 • Some emotional problems: moderate level of functioning impairment - 3 • No known problems - 0	Anomie/Strain
Peers	• Criminal influences and associates - 6 • Negative associations or influences: Loner - 3 • Supportive positive influences - 0	Social Bond (Control) Social Learning (Differential Association) Anomie/Strain
Recreation/Hobby	• Not participating in constructive leisure time activities, hobbies or regular physical activity - 1 • Participating in positive recreational activities/hobbies - 0	Social Bond (Control)
Organization/Social Affiliation	• Not involved in any positive extracurricular social groups - 1 • Involved in positive organization/social affiliation - 0	Social Bond (Control) Anomie/Strain
Health	• Serious handicap or chronic illness - 2 • Handicap or illness interferes with functioning - 1 • Sound physical health - 0	Anomie/Strain

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