5-2024

A Comprehensive Examination of the Post-Conviction Risk Assessment (PCRA) and Risk Prediction Index (RPI) for General Risk Factors, Criminogenic Outcomes, and Risk-Specific Populations

Logan J. DiStasio

THE UNIVERSITY OF NEW HAVEN

A COMPREHENSIVE EXAMINATION OF THE POST-CONVICTION RISK ASSESSMENT (PCRA) AND RISK PREDICTION INDEX (RPI) FOR GENERAL RISK FACTORS, CRIMINOGENIC OUTCOMES, AND RISK-SPECIFIC POPULATIONS

A THESIS

Submitted in partial fulfillment

of the requirements for the degree of

MASTER OF SCIENCE IN CRIMINAL JUSTICE

BY

Logan DiStasio

University of New Haven
West Haven, Connecticut
May 2024

A COMPREHENSIVE EXAMINATION OF THE POST-CONVICTION RISK ASSESSMENT (PCRA) AND RISK PREDICTION INDEX (RPI) FOR GENERAL RISK FACTORS, CRIMINOGENIC OUTCOMES, AND RISK-SPECIFIC POPULATIONS

APPROVED BY

David L. Myers

[David Myers, Ph.D.]
Thesis Adviser

Maria Tcherni-Buzzeo
Maria Tcherni-Buzzeo (May 9, 2024 12:43 EDT)

[Maria Tcherni-Buzzeo, Ph.D.]
Committee Member

John DeCarlo

[John DeCarlo, Ph.D.]
Committee Member & Program Coordinator

[Mario T. Gaboury, Ph.D.]
Dean of the College

Nancy O. Savage
Nancy Savage (May 19, 2024 14:44 EDT)

[Nancy O. Savage, Ph.D.]
Provost

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to Dr. David Myers for his unwavering support and invaluable mentorship throughout the duration of this project. His guidance and expertise have been instrumental not only to the success of the current research but also in shaping my personal and professional growth. My accomplishments in these pursuits would not have been possible without him. Furthermore, I extend my sincere appreciation to Dr. Maria Tcherni-Buzzeo and Dr. John DeCarlo for their insightful contributions to this thesis. There is no doubt that their expertise, review, and support have greatly enriched the project as a whole. Lastly, I would like to thank the members of the United States Probation and Pretrial Services division for the District of Connecticut for allowing me to conduct interviews as part of this research. The division's commitment to fostering collaboration and promoting academic inquiry is truly commendable. I am grateful for the illuminating perspectives they have shared.

Abstract

The use of risk assessment instruments has become an increasingly pertinent issue in the realm of reentry. Though sometimes controversial, risk assessment tools provide local, state, and federal governments with actuarial techniques focused on providing unbiased and accurate risk assessments for individuals returning to the community. The present study was focused on the further evaluation of two risk assessment instruments utilized by the Administrative Office of the United States Courts (AOUSC)—the Post-Conviction Risk Assessment (PCRA) and the Risk Prediction Index (RPI). A mixed-methods approach was taken in order to investigate the associations between these tools, general risk factors, criminogenic outcomes, and more risk-specific populations. Utilizing data from a study previously focused on examining a federal reentry program, the results showcased several notable findings. This included the discovery of statistically valid associations between the PCRA and all diverse criminogenic outcomes examined. Among the various risk factors, housing instability stood out due to its association with outcomes, but not with risk assessment instruments. This finding suggests that housing instability may not be adequately integrated within the PCRA or RPI. Furthermore, based on qualitative interviews, federal probation officers possessed a noticeable degree of trust in the PCRA, but they also still believed there was potential for improvement. There were less favorable views of the RPI. Overall, the results of this study suggest the PCRA is a useful tool for federal reentry programming. Despite the progress made in this area of study, there remains ample room for continuing the validation process and expanding the comprehension of complex assessment, supervision, and treatment processes.

Keywords: Federal risk assessment, risk factors, reentry, risk-needs-responsivity, PCRA, RPI, mixed-methods, validity, recidivism

TABLE OF CONTENTS

LIST OF TABLES

INTRODUCTION

The field of federal probation and post-release supervision has struggled historically with reducing rates of recidivism. Past research has found that up to 50% of federal inmates recidivate within 8 years of release (Hunt & Dumville, 2016). Indeed, this problem has persisted even through landmark policies designed to help mitigate the large percentage of inmates who experience reincarceration (Cotter et al., 2021). This population, estimated to include as many as 160,000 inmates, largely consists of individuals convicted of drug, weapon, and sex offenses (Federal Bureau of Prisons, n.d.). The reality is that a large majority of these individuals will eventually return to the community. This understanding provides special considerations for the numerous economic and social barriers faced by federal offenders upon their reentry. These issues necessitate a more thorough assessment of how the Administrative Office of the United States Courts (AOUSC) Probation and Pretrial Services Division can effectively address the reintegration of ex-offenders back into the community.

One practice currently in place to assist federal probation officers in supervising the reentry process is the use of actuarial risk assessment tools. At its core, actuarial risk assessment is the process of evaluating and assigning offenders to different groups based upon the predicted risk of future criminal behavior (e.g., Grove & Meehl, 1996; Hart et al., 2007; Silver & Miller, 2002). This process occurs through the calculated composition of static and dynamic risk factors. Static risk factors are elements of an offender's life that are unalterable, such as a prior criminal record or demographic variables. Dynamic factors are variables in an individual's life that are changeable, such as an individual's social network or a drug and alcohol addiction. Broadly speaking, federal risk assessment tools have been implemented in order to support the risk-needs-responsivity principles of offender reentry and to enhance the efficacy and efficiency of pre- and post-conviction supervision (Johnson et al., 2011). These efforts are ultimately undertaken to maintain the community's safety and security.

Two widely utilized risk assessment tools in the realm of federal reentry assessment are the Risk Prediction Index (RPI) and the Post-Conviction Risk Assessment (PCRA). The RPI, a second-generation risk assessment tool, has diminutive empirical insight as to the strength of its model. However, the scant research that does exist generally reveals acceptable validity and dependability (Eaglin et al., 1997; Lombard & Hooper, 1998). Alternatively, the PCRA, a fourth-generation tool, has a more robust background of research investigating its functionality. Indeed, several studies have found that the PCRA demonstrates predictive accuracy (e.g., Johnson et al., 2011; Lowenkamp et al., 2013, 2015). Despite a more extensive background of validation studies, there are a few critical points to consider.

To begin, a majority of studies validating the PCRA have only utilized measures of re-offending as the outcome variable (e.g., Johnson et al., 2011; Lowenkamp et al., 2013, 2015; Luallen et al., 2016). Although the initial design of the PCRA dictates rearrest as the easiest and most viable way to comprehend recidivism, other crucial outcomes are omitted. For instance, it has long been understood that drug abuse and/or relapse are significant indicators of future antisocial behavior (Bennett et al., 2008; Dowden & Brown, 2002). Despite this finding, research validating the PCRA has yet to address the full possibility of insight gained from comprehending the relationship between risk factors, risk assessment tools, and diverse criminogenic outcomes. Indeed, recent literature has called attention to the significance of examining the diverse behavioral outcomes of justice-involved individuals outside of the sole use of measures of reoffending (Klingele, 2019).

Additionally, the populations utilized as a part of previous measures attempting to validate the PCRA have been skewed largely towards a classification of individuals with lower probabilities of recidivism. This presents an issue given that, although it may be representative of other more general population risk scores (Lowenkamp et al., 2013), additional discernment of the relationships between risk factors and risk assessment tools for those deemed higher risk is not well understood. Finally, there is a lack of research matching quantitative data with the perceptions of the very individuals involved in utilizing these specific types of instruments. Indeed, the benefits of gaining insight into issues related to incarceration and reentry from the perspectives of the criminal justice authorities who deal with these challenges on a daily basis are axiomatic. A few projects in the past have produced valuable implications through their evaluation of criminal justice officials' attitudes, particularly those related to risk assessment tools and practices (Fitzgibbon et al., 2010; Mair et al., 2006; Viglione et al., 2015). In all, these considerations leave open the possibility of understanding risk factors, risk assessment tools, and criminogenic outcomes on a more precise level.

The current study intended to address present gaps in the existing literature by closely examining the relationships between risk factors, the PCRA and RPI, and criminogenic outcomes. Specifically, this study addresses both the actual and perceived associations between these three separate phenomena. An explanatory sequential mixed methods design was used, involving the use of quantitative secondary data, and then supplementing the quantitative results with subsidiary qualitative data. In the first quantitative phase of the study, findings were produced by analyzing data from a study of a federal reentry program in the state of Connecticut. The second qualitative phase was conducted as a follow-up to the quantitative analysis to produce additional findings and help explain the quantitative results.

In the qualitative component, federal probation officers were interviewed to understand their perceptions of risk factors, risk assessment tools, and criminogenic outcomes associated with federal reentry. This approach was intended to provide a more nuanced understanding of the link between the processes of risk assessment and those individuals who are deeply involved with their utilization and subsequent outcomes. Overall, the findings produced should serve to clarify future avenues for more advanced federal risk assessment instruments and, in turn, help devise more complex strategies for further reducing recidivism.

The following literature review will detail the composition of risk factors and assessments in the field of criminal justice. A brief discussion of the purpose and theoretical underpinnings of risk assessment will occur. A subsequent section will explain the context and growing call for discerning diverse criminogenic outcomes, followed by an examination of the history of federal risk assessment tools and the current state of research and practice for the PCRA and RPI. Following the literature review, the methodology and findings of the current research will be presented, and the study will conclude with policy and research implications.

LITERATURE REVIEW

Despite its complexity, risk assessment has become the cornerstone of many criminal justice practices today. However, it can often be difficult to conceptualize its contents and processes adequately, given the variability in construction, purpose, implementation, and validity. Indeed, the milieu surrounding risk assessment often hinders greater efficiency and perceptions of its operations (Silver & Miller, 2002). Nevertheless, use of risk assessment and analysis has grown in popularity over the past 40 years (Aven, 2016). For example, Singh et al. (2014) found that over 200 different risk assessment tools are utilized across the world to examine and calculate risk. Modern revision of the Model Penal Code, which partially entails directing the U.S. Sentencing Commission to expand and foster the use of actuarial risk assessment tools, has spurred the growth and practice of applying these types of tools for both reentry and pre-conviction supervision across the United States (Garrett & Monahan, 2019; Monahan & Skeem, 2016; Reitz & Klingele, 2019). Overall, it is increasingly evident that risk assessment has been widely adopted and endorsed by federal, state, and private organizations across the country.

Characteristics of Tools

Though risk assessment tools vary in their components, there are a few common principles that dictate their framework and purpose. Risk assessment can be defined broadly as the process of: (1) gathering evidence; (2) building a foundation of knowledge based on that evidence; (3) conducting risk evaluation; (4) filtering outcomes through decision-makers' perspectives; and (5) reaching a final decision (Aven, 2016; Hansson & Aven, 2014). In the context of criminal justice, actuarial risk assessment is generally understood to be an extension of these principles related to making decisions about justice-involved individuals' futures (Bonta

& Andrews, 2016). All actuarial risk assessment tools include the use of risk factors to help create a composite score aimed at placing an offender into a certain risk category. Additionally, all criminal justice-related actuarial risk assessment tools are employed either pre- or post-conviction. Generally, research has tended to focus more on post-conviction risk assessment, rather than pre-trial risk assessment (Cadigan et al., 2012).

Despite shared similarities, there are also a few key differences in the use of actuarial risk assessment tools in the realm of criminal justice. In particular, Monahan and Skeem (2016) contend there are three main differences: desired outcome, structure, and validity. Desired outcome, or scope, refers to what a risk assessment tool is ultimately attempting to achieve. The foremost purpose of many risk assessment tools (especially those used in the pretrial phase) is to predict future recidivism. For example, a popular tool implemented within the state of Colorado's judicial system, known as the Colorado Pretrial Assessment Tool (CPAT), has the expressed goal of measuring "the defendant's risk of failure to appear (FTA) or re-arrest while released pretrial" (Terranova & Ward, 2020, p. 8). Although this statement may hold true for the CPAT and other pretrial evaluation tools, this goal is not ubiquitous. It is worth noting that many other risk assessment instruments employ expanded metrics dedicated to forecasting the likelihood of recidivism/rearrest, while also providing ancillary insights to assist in identifying potential aggravating factors that can be addressed during the subsequent stages of rehabilitation and reentry (e.g., the Correctional Assessment and Intervention System; National Council on Crime and Delinquency, 2006).

Structure refers to the tendency of risk assessment tools to vary in their construction. All risk assessment tools are built with several considerations in mind. Examples of these considerations include, but are not limited to, the scoring of individual and composite measures, the computation of recidivism risk, and the scope of discretionary evaluation (Monahan & Skeem, 2016; Skeem & Monahan, 2011). Individual and composite measures detail the categories that ultimately are used for scoring. These measures are the various risk factors included in a risk assessment tool. Regarding the risk factors themselves, risk instruments differ in both their use and operationalization. The actual method by which an instrument prioritizes and aggregates these different factors may also differ.

Furthermore, risk assessment tools will vary depending on the range of judgment afforded to their operator(s) (Hannah-Moffat et al., 2009; McCafferty, 2017; Monahan & Skeem, 2016). For example, some tools tend to grant their users a wide range of discretion based on their calculations and output, such as the Level of Service/Case Management Inventory (LS-CMI; Andrews et al., 2004), which includes several in-depth processes meant to consolidate risk assessment with case management by allowing probation officers to be more involved in the risk assessment process. Meanwhile, other actuarial tools may produce a score and resolution with little input or consideration from the users themselves, such as the Static 99, which is solely focused on predicting the future risk of sexual recidivism (Hanson & Thornton, 1999). Taken together, these constituents provide a wide range of possibilities in the arrangement and use of risk assessment tools.

Lastly, there is the validation of risk assessment instruments. As a natural consequence of deviations in scope, structure, and funding, risk assessment tools have differing degrees of empirical validation (Desmarais et al., 2018; Monahan & Skeem, 2016). Studies analyzing risk assessment tools tend to either focus on individual risk assessment tools themselves or on more broad groupings of instruments categorized by common components (Desmarais et al., 2021; Latessa et al., 2010). Additionally, some tools have a long history of empirical scrutiny, while others have little to no empirical oversight. Along with the number of studies validating specific instruments, the quality and rigor of studies attempting to validate tools also differ significantly. This is important to acknowledge because the use and implementation of risk assessment tools should depend heavily on previous evidence-based practices. Despite a large variety of risk assessment instruments and the numerous validation studies conducted on them, no one tool has been found to significantly outperform the others in terms of forecasting accuracy or performance (Desmarais et al., 2021; Monahan & Skeem, 2016). Understanding the nuances of risk instruments (including their similarities and differences) helps inform policymakers, researchers, and stakeholders alike, providing the grounds for advancement in the field of risk assessment.

Purpose and Theory

Several key theoretical conceptualizations serve as the foundation for the implementation, operation, and rationale behind risk assessment instruments. Arguably, the most germane theoretical framework employed in understanding the application of risk assessment tools is the Risk-Needs-Responsivity (RNR) model (Bonta & Andrews, 2016). Although the RNR model has been criticized as a result of its ambiguous organization (Fortune & Heffernan, 2019; Polaschek, 2012; Taxman et al., 2006; Ward et al., 2007), its application has proven to be useful in a variety of rehabilitative environments (e.g., Dowden & Andrews, 2003; Singh, Desmarais, Sellers, et al., 2014; Smith et al., 2009). The RNR model is tied closely to assumptions consisting of the need for rehabilitative and risk-identification contexts, specifically during the process of reentry from incarceration. According to Ward et al. (2007), the RNR model can be broken down into three distinct sections: general utility, etiological construction, and pragmatic application.

The RNR model emphasizes the significance of minimizing any potential harm caused by an offender's behavior. It contentiously places a preponderance of the focus on reducing harm to society rather than the rehabilitation of an offender (Ward et al., 2007). In addition, the RNR model also draws on a perspective that acknowledges the multifaceted nature of criminal conduct (Bonta & Andrews, 2016). This means individual contexts should be considered when understanding the sophisticated processes affecting criminal activity. Due to the complexity of elements influencing deviant behavior, successful treatment must be thorough in addressing the issues most likely to result in the greatest chances of lowering the likelihood of reoffending. Indeed, the scarcity of resources within criminal justice systems requires the systematic targeting of factors commensurate with risk prediction levels for maximum efficiency in the supervision process (Bonta & Andrews, 2007).

Beyond their general applicability, Bonta and Andrews' three distinct works, The Psychology of Criminal Conduct (PCC), General Personality and Social Psychological Perspective on Criminal Conduct (GPSPP), and Personal Interpersonal Community-Reinforcement Perspective (PIC-R), serve as the foundation for RNR's etiological assumptions (Andrews, 1982; Bonta & Andrews, 2016; Ward et al., 2007). The PCC, GPSPP, and PIC-R build on one another to create an all-encompassing network of explanatory variables that attempt to describe the mechanisms responsible for criminal conduct. While the explanatory frameworks for these writings are not necessarily original, they work to combine several other popular criminological theories into one set of contentions aimed at explaining criminal activity and rehabilitative practices. Indeed, many of the etiological explanations utilized by Bonta and Andrews (2016) are drawn from social learning, rational choice, and routine activity theories.

Although a more detailed explanation of the theoretical underpinnings of RNR is beyond the scope of the current paper, they play a crucial role in the motivations of this model.

Arguably, the most well-known aspect of the RNR model is its application for reentry and rehabilitation programs. Indeed, RNR has played a distinct role in the development of risk assessment instruments. One of the most popular risk assessment tools today, the Level of Service/Case Management Inventory (LS-CMI; Andrews et al., 2004), was a direct result of the work conducted to establish RNR principles. At its most fundamental level, RNR refers to three major factors to consider for best practice when focused on offender reentry.

The *risk* principle refers to the idea that everyone has some amount of potential risk present and that those who are higher risk should be the focus of rehabilitative programs. The *needs* principle of RNR refers to the importance of targeting the antisocial elements inherent in potential reoffenders. Eight major criminogenic factors known as the "central eight" are often defined as most pertinent to future criminal behavior (Andrews et al., 2006; Bonta & Andrews, 2016). They include a history of antisocial behavior, antisocial personality patterns, antisocial cognitions, antisocial associates, family/marital circumstances, education/employment, leisure/recreation, and substance abuse. Finally, the *responsivity* principle emphasizes the importance of tailoring techniques designed to intubate risk and needs principles conducive to accurately addressing the unique concerns of criminal culpability. These principles, taken together, formulate the operationalization of RNR's core theoretical principles. Ultimately, a significant portion of the RNR model is concerned with the detection and utilization of risk factors, which has contributed greatly to the development of risk assessment tools.

What Are Risk Factors?

As was previously mentioned, risk factors can be challenging to understand because their assumptions and operationalizations tend to differ depending on the risk assessment instrument being employed. However, these factors can be commonly understood as variables that indicate a susceptibility to potential future criminality (Kraemer et al., 1997). Traditionally, risk factors have been grouped into two overarching classifications: static and dynamic. Being the first to develop in risk assessment and the easiest to use for calculation, static characteristics have continued to supplement the development of their actuarial risk instrument counterparts. On the other hand, dynamic factors are more difficult to operationalize and have progressed at a slower rate in the process of helping to build more advanced risk assessment instruments.

Nonetheless, the literature has steadily worked to refine these categorizations (Kraemer et al., 1997; Monahan & Skeem, 2014, 2016). For the purpose of the current research, these expanded classifications will be compartmentalized into two main classes: *advisory* and *mutable*. Advisory factors are those that are not susceptible to modification and include both fixed and variable-level subcategorizations (Kraemer et al., 1997; Monahan & Skeem, 2014, 2016). Fixed risk factors are properties of an individual that cannot be addressed or changed, no matter the circumstance. For example, prenatal complications would qualify as fixed risk factors because they are immutable and have been linked to future deviant behavior (Olds, 2008; Tibbetts & Rivera, 2015). Variable indicators are factors that cannot be addressed by treatment but are subject to change. A popular example of a variable indicator is age (e.g., Farrington, 1986).

Mutable risk factors are elements that can be addressed by interventions. This grouping includes malleable and causal risk factors. Malleable risk factors are features that have demonstrated change when applying an intervention but still lack the appropriate evidence to establish a causal link between the reduction of risk and the variable factor. For instance, although low income is frequently correlated with a higher likelihood of criminal activity (Bjerk, 2007; Hay et al., 2007; Jarjoura et al., 2002), there is yet to be direct evidence to suggest a causal association with risk intervention (Heller et al., 2010; Løken et al., 2012). Lastly, causal risk factors are both changeable and have a direct causal relationship with reducing risk. A handful of studies have worked to identify possible causal mechanisms for risk intervention. One grouping of potential causal risk factors identified by research includes antisocial attitudes and beliefs (Ashford et al., 2008; Kroner & Yessine, 2013; Olver et al., 2007; Papalia et al., 2019).

These matrices provide the schematics for current risk factors. Understanding different categorizations of risk factors helps demystify the structure and purpose of many risk assessment tools. In general, risk factors are the building blocks for effective risk assessment. However, their eclectic nature has caused wide speculation as to the most predictive variables and in what context they work best. Risk factor groupings such as the "central eight" are touted as being the most applicable building blocks for risk assessment (Bonta & Andrews, 2016). Other scholars contend that such a grouping may not be as constructive as indicated and that its relevancy is dependent on several other factors, including age and type of offense (Mei et al., 2021; Van Horn et al., 2018; Via et al., 2016; Wilpert et al., 2018). These differences showcase a clear need to further investigate the associations risk factors have with multiple risk assessment processes, including the instruments themselves, and another crucial aspect of the application of risk assessment: specific outcomes.

Criminogenic Outcomes in the Context of Reentry

A key element in understanding and improving risk assessment is the modus operandi practitioners wish to use when examining outcome measures and program success. As stated earlier, specific outcome measurements and goals related to the use of risk assessment tools vary on a case-by-case basis. However, the bulk of risk assessment tools use recidivism as their key performance indicator. Indeed, the popularity of utilizing recidivism as a measure of programmatic and instrument success has been well-established among practitioners, government officials, and researchers alike (Klingele, 2019). However, despite this longstanding use, concerns have been raised in the community that challenge the usefulness of this extant measurement.

The first major issue identified with the use of recidivism as the sole outcome measure of a program or instrument pertains to characterization challenges. Indeed, recidivism has been and is still measured and conceptualized in several ways. For example, according to Johnson (2017), the AOUSC defines recidivism as "the first rearrest for new criminal activity that occurs during and after an offender's term of supervision" (p. 53). Meanwhile, while conducting a study investigating the exploratory power of the interactions between community and race in predicting recidivism, Wehrman (2010) defined recidivism as "the presence of a follow up felony conviction" (p. 541). Rearrest and receiving a felony conviction are two distinct processes of the criminal justice system that do not always intersect. A lack of definitional clarity adversely affects the ability to determine what programs and risk assessment instruments work best, because differing definitions often lead to alternative operationalizations of variables and results.

Beyond a more cohesive coalition for recidivism classification, there are also concerns related to the processes by which recidivism is defined. For example, due to its inability to effectively assess a comparative level of criminal culpability, the use of conviction rates as an indicator of recidivism is often seen as dubious (Klingele, 2019; Ruggero et al., 2015). This is because judicial proceedings sometimes make it difficult to evaluate adequately whether an actual conviction (or lack thereof) was based on criminal behavior. Cases may be dismissed on technical grounds even when the defendant is truly guilty of a crime, and individuals may be convicted when they are actually innocent. Indeed, it is estimated that up to 3% of felony cases involve a wrongful conviction (Ramsey & Frank, 2007). Furthermore, a majority of wrongful convictions in the United States are tied to disparate racial biases, with Black people disproportionately being wrongfully convicted at higher rates than other races (Gross et al., 2022). These issues make the utilization of conviction rates questionable as an indicator of risk assessment instrument success.

These weaknesses are also indicative of an overarching concern with the current use of recidivism measures for outcome success. That is, they fail to encapsulate the complete extent of criminogenic behaviors. Ultimately, these measures are representative of a one-dimensional analysis trying to explain a multi-dimensional phenomenon. It has become more apparent as criminological research has evolved that criminal behavior is not the result of any singular characteristic. Instead, it is believed that a matrix of factors influences criminal activity (Bonta & Andrews, 2016). Therefore, measuring behavior through the sole use of a punitive outcome (e.g., getting rearrested or reconvicted) limits understanding of the inherent power and complexity of situational/individual characteristics. A balance must be struck between attempting to measure future deviant behavioral outcomes and more complex measurements of prosocial behaviors, so that a wider and more appropriate range of results can be assessed. Similarly, reimagining and redefining “successes” in reentry outcomes allows for more specific performance indicators and, consequently, more clarity in what areas of reentry require the most attention from policymakers (King & Elderbroom, 2014). In doing so, relevant parties will gain a more comprehensive picture of risk instrument prediction success.

Federal Risk Assessment

The history and evolution of federal risk assessment tools have been generally well documented. They first came to fruition with the establishment of the Probation Act of 1925, which enacted the possibility of probation as a sentence in the federal court system. In the beginning, the federal government relied on the exclusive discretion of criminal justice practitioners to measure and analyze the risk of reoffending and/or noncompliance among felony offenders. However, it became apparent shortly after its establishment that implicit and explicit factors often influence practitioner judgment (e.g., Brennan et al., 2009; Grove & Meehl, 1996; Hastie & Dawes, 2009).

In addition, though still somewhat contentious, more recent scientifically rigorous research finds that actuarial tools are better suited toward predicting future risk. For example, Wertz et al. (2023) utilized a sample of 416 reports to compare structured and unstructured clinical assessments of future risk. In order to assess the difference between the two, they utilized the area of the curve-receiver operating characteristics (AUC-ROC). The AUC-ROC is a popular diagnostic test useful for determining the number of true and false positives and negatives. In using AUC-ROC as their point of analysis, they found that actuarial evaluation had a larger effective size of r =.66 for general criminal recidivism, while unstructured analysis was r =.59. However, the most noticeable discrepancy in effect sizes in the study was the difference in predicting violent crime, in which unstructured judgment scored an r =.52 and the actuarial instrument utilized scored an effect size of r =.71. These findings suggest that completely unstructured criminal justice risk assessment is not the most effective application of risk assessment, and that actuarial tools are necessary to better predict future risk. Although more advanced risk assessment tools would not be built until much later, early burgeoning ideas about how to better address the prediction of risk among ex-offenders led to the second generation of risk assessment instruments.

The second generation of risk assessment tools originated in the Illinois court system, where it was first surmised that certain characteristics of an offender's profile could help differentiate between whether their parole was a "success" or "failure" (Burgess, 1936). Though rudimentary in scope, for the first time in the history of the United States, static risk factors were utilized to help inform judgments of future risk. These risk assessment instruments utilized static risk factors to score and measure different elements considered to increase the chances of reoffending. A few examples of the initial and most frequently employed static factors include information on previous convictions, family ties, gender, and age (Bonta & Wormith, 2007).

The use of static factors for second-generation risk assessment instruments was an important step in increasing the utilization of non-biased tools that promoted some semblance of evidence-based factors to help guide the decision-making process. Although only elementary in the evolution of risk assessment development, several studies have shown the utility of risk assessment tools entirely designed by computing static risk factors (e.g., Caudy et al., 2013; Grove & Meehl, 1996; Hanson & Thornton, 1999). However, as time progressed, a need arose to address the myriad of complications produced by the use of static factors for risk assessment. Notably, scholars have critiqued risk assessment tools that only use static factors for their inability to address dynamic (changeable) risk factors, their inability to integrate with case management, and their somewhat questionable connection with theoretical underpinnings (Brennan et al., 2009). These limitations eventually led to the third generation of risk assessment instruments.

Third-generation tools combine both static and dynamic risk factors to better address the complexity of behavior involved in criminal offending. Third-generation risk assessment instruments aim to acknowledge and incorporate mutable characteristics in a manner that works to predict risk more effectively. They were also developed to better address risk factors through individualized and targeted rehabilitation. This movement was greatly inspired by the theoretical work of the RNR model developed by Bonta and Andrews (2016).

Indeed, one of the earliest third-generation risk assessment tools developed was Andrews and Bonta's (2000) Level of Service Inventory-Revised, or LSI-R. A wealth of research has shown that the LSI-R and other similar third-generation risk assessment tools are effective at predicting future offending and often outperform second-generation instruments (Campbell et al., 2009; Chu et al., 2013; Gendreau et al., 1996; Schwalbe, 2007). Although a useful step in the progression of risk assessment tools, third-generation practices were censured for their lack of diverse etiological explanations, their inability to address gender and racial bias, their tendency to emphasize prediction of risk over treatment, and their omission of important responsivity principles (e.g., Andrews et al., 2006; Reisig et al., 2006; Zhang & Han, 2022). Eventually, research and analysis of third-generation instruments led to the latest evolution of tools officially deemed fourth generation.

Fourth-generation instruments are mainly characterized by their emphasis on integrating risk assessment data into case management systems (Andrews et al., 2006). These tools are designed specifically with the idea that risk assessment should further encapsulate the complex systems of rehabilitation and treatment. Beyond a stronger connection to case management systems, fourth-generation risk assessment tools are meant to address previous concerns of older-generation instruments by incorporating a more diverse array of theoretical insights. They also include a mix of evidence-based factors with more elaborate actuarial measurements. A few common fourth-generation risk assessment tools include the Level of Service/Case Management Inventory (LS/CMI; Andrews et al., 2004), the Correctional Offender Management Profiling for Alternative Sanction (COMPAS; Northpointe Institute for Public Management, 1996), and the Ohio Risk Assessment System (ORAS; Latessa et al., 2010).

Though there is currently an insufficient amount of research comparing the newer generation of instruments to their older counterparts, limited studies have found them to be more successful in their predictive capabilities depending on outcome measurement (Andrews et al., 2006; Campbell et al., 2009). However, more research is needed to understand the full extent of projective strengths and the practicality of newer-generation tools. Furthermore, despite a lack of research directly measuring predictive proficiency, it has been postulated that the inclusion of case management with actuarial and structured judgment allows for a seamless application of diverse intervention capabilities and service delivery (Andrews et al., 2006). Given the challenging nature of utilizing risk assessment in rehabilitation practices, a clear and direct understanding of the benefits produced by these tools may be more difficult to operationalize sufficiently.

In summary, the design, function, and scope of risk assessment instruments have experienced numerous evolutions. The progression from practitioner discretion to static criteria, to incorporating dynamic elements, and to the integration of risk factors with case management has not been particularly straightforward. Indeed, despite compelling arguments in favor of tools from more recent iterations, components from all four generations are still being used and validated in reentry contexts. In addition, a new fifth generation of instruments has been speculated to exist, which are distinguished by enhanced sophistication and automation of risk estimation and prediction (Koetzle Shaffer et al., 2011; Lovins et al., 2018; Wormith, 2017). Nevertheless, these instruments have yet to be extensively implemented or validated, particularly in a federal context. Most federal risk assessment tools are either second, third, or fourth generation. Two of these specific tools are the Risk Prediction Index (RPI) and the Post-Conviction Risk Assessment (PCRA).

Risk Prediction Index (RPI)

The RPI, an antecedent to the PCRA, was originally implemented to meet the need for a more accurate risk-prediction model (Administrative Office of the United States Courts Probation and Pretrial Services Office, 2018). It is made up of eight different risk variables in the form of primarily binary responses and scoring (Lombard & Hooper, 1998). The majority of these variables fall under the category of malleable risk factors. The items on the RPI include: (1) age at the start of supervision; (2) number of prior arrests; (3) whether a weapon was utilized in the offense; (4) current employment status; (5) history of drug and alcohol abuse; (6) whether an individual attempted to elude supervision; (7) the presence or absence of a college degree; and (8) whether an individual is living with a spouse and/or children at the beginning of supervision. These items have a total score ranging from 0 to 9. As is typical of other similar risk assessment tools, lower scores are associated with a lesser likelihood of recidivism, while higher scores indicate a greater chance that the individual will recidivate. According to the AOUSC, the main purpose of the RPI is to assist federal officers with case management (Administrative Office of the United States Courts Probation and Pretrial Services Office, 2018), although the precise method by which the RPI is to be used by officers is relatively equivocal (VanBenschoten, 2008).

A few studies constitute the creation and validation of the RPI. First, a sample of 2,651 supervision cases from 1989 was utilized to collect data and build the RPI (Eaglin et al., 1997). Subsequent analysis performed by Eaglin et al. (1997) showcased an improvement in recidivism prediction scores compared to an older risk assessment tool that was used by the AOUSC at the time. They found that those who scored 0-2, 3-5, and 6-9 had recidivism rates of 10.5%, 38%, and 53.4%, respectively. Additional steps were taken to validate the RPI further by field-testing its efficacy in 11 different federal districts. By utilizing a verification sample of 278 people, Lombard and Hooper (1998) found that RPI score patterns were relatively uniform with what was expected. Overall, the correlation coefficient between RPI risk scores and recidivism outcomes produced in the later research was higher than the original validation techniques applied for the RPI's creation (.54 compared to an average of .38). Despite the increased predictive accuracy of the RPI, several key limitations eventually led to the creation of the PCRA. The most notable was its exclusive use of static factors (*IBM Strategic Assessment*, 2004). This issue, along with others, ultimately led to the formation and development of the PCRA.

Post-Conviction Risk Assessment (PCRA)

The PCRA is divided into two distinct sections, the first of which is commonly known as the officer assessment. It involves scoring by federal probation officers. The officer assessment is split between seven separate risk factor subcomponents, which include criminal history, education/employment, substance abuse, social networks, cognitions, violence assessment, and responsivity factors. These domains contain a total of 63 distinct risk elements; 25 of these items are scored, while the other 38 are not. The scored factors for each subcomponent are distributed between six scored items in the criminal history section, three scored items in the education/employment section, two scored factors for the substance abuse section, three scored factors for the social networks section, a single scored factor for cognition, and 10 items for the violence assessment section. Among the criteria that are not scored, there are three items related to substance abuse, two items involving social networks, 12 items for cognitions, seven items regarding violence assessment, and 17 items about responsivity factors.

According to the AOUSC's Probation and Parole Services, the purpose of utilizing unscored factors is to help guide concluding judgments regarding barriers to reentry and for data collection purposes (Administrative Office of the United States Courts Probation and Pretrial Services Office, 2018). Overall, research finds that integrating unscored sections of the PCRA does not significantly improve prediction accuracy (Cohen & Bechtel, 2017). At the end of the scoring process, point totals are added, and the individual is placed into a subsequent risk category. It is important to note that officers are given the opportunity to "override" risk categorizations produced by the PCRA. However, Cohen et al. (2020) found that these overrides tend to adjust the risk prediction index inaccurately for an offender, and thus, they should not be relied upon in the active duty of probation officer risk management.

The second section of the PCRA includes offender assessment. This component is a self-evaluation used to gauge criminal thought patterns. Specifically, it is modeled after the Psychological Inventory of Criminal Thinking Styles (PICTS; Walters, 1997). The PICTS is an 80-item evaluation designed to assess several types of cognitive archetypes through the use of a sophisticated algorithmic assessment protocol. The PICTS has been validated across several different studies (e.g., Walters, 2002, 2012). This includes efforts to assess the PICTS predictive accuracy in samples of federal offenders (Walters & Cohen, 2016; Walters & Lowenkamp, 2016). Ultimately, the offender assessment section assists practitioners by offering projected cognitive frameworks. By understanding an individual's current deviant thinking habits, practitioners can tailor specific strategies to address that pattern. For example, cutoff, a type of deviant cognition employed by offenders to minimize deterrence, is often linked to anger, which may be addressed through anger management cognitive behavioral therapy (Henwood et al., 2015; Walters & White, 1989).

Validity and reliability estimates of the PCRA have been demonstrated through numerous studies (e.g., Johnson et al., 2011; Lowenkamp et al., 2013, 2015). The tool was first constructed and validated utilizing a sample of 185,297 offenders on federal probation or supervised release (Johnson et al., 2011). Johnson et al. (2011) employed multivariate logistic regression models and bivariate cross-tabulations to determine the relevance and weight of risk predictors. To determine instrument effectiveness, they utilized AUC-ROC, survival analysis, and cross-tabulations. The AUC-ROC scores generated by Johnson et al. (2011) ranged from .709 to .783, which falls under an acceptable interpretation (Nahm, 2022). The survival analysis rates corresponded with expectations for the different risk-level categorizations. By the end of 60 months of supervision, offenders deemed low, low/moderate, moderate, and high-risk had a survival rate of 85%, 58%, 25%, and 6%, respectively. Similarly, cross-tabulations conducted between risk category and new arrest percentage between low, low/moderate, moderate, and high-risk were 11%, 42%, 71%, and 83%, respectively. These results confirmed the ability of the PCRA to classify individual risk categorizations at an acceptable level.

Additional analysis conducted by Lowenkamp et al. (2013) sought to validate the PCRA further through the utilization of several analytical techniques, including, but not limited to, interrater agreement, multivariate logistic regression models, and AUC-ROC on a new sample of cases. Ultimately, they discovered that the PCRA offers sufficient predictive validity for both short- and long-term follow-up periods. After these initial efforts, subsequent studies would revalidate these results, while also confirming their utility as a predictor of violent behavior and criminal career outcomes (DeLisi et al., 2018; Lowenkamp et al., 2015; Luallen et al., 2016). Furthermore, despite worries about potential discrimination produced by risk assessment instruments, studies have generally agreed that the PCRA does not hold gender or racial biases (Lowenkamp et al., 2015; Skeem & Lowenkamp, 2016).

While validations and considerations of the use of risk assessment tools continue to grow more sophisticated, specific data related to the PCRA and the RPI presently lacks a few important considerations when analyzing their effectiveness. Specifically, a significant portion of prior research has failed to account for the degree to which these instruments might forecast varied criminogenic consequences. As explained in the criminogenic outcome section, the utility of understanding the propensity of federal risk assessment instruments to predict diverse outcomes may help broaden the scope of their capability.

Additionally, studies evaluating the effectiveness of these tools have largely validated instruments exclusively in populations that fall under low to low/moderate risk categories. This trend is important to address because there is a possibility that a study evaluating a population of offenders who are deemed to be at higher risk might showcase differing effectiveness of risk assessment instruments. Finally, little research to date has considered the impact of probation officers' perceptions on the use of these instruments. Amplifying the voices of practitioners who utilize risk assessment instruments every day may help bring to light pressing concerns related to their operation. This research is particularly pertinent given the possibility of practitioner skepticism about the ability of federal risk assessment tools to accurately predict future risk assessment, effectively undermining their purpose and leading to increased accounts of manual overrides (Taxman, 2018; Viglione et al., 2015).

The current study seeks to contribute to the literature on this problem by addressing these concerns and attempting to revalidate these tools as they relate to general risk factors and distinctive criminogenic outcomes. The proposed research will examine a unique sample of federal offenders released in the state of Connecticut. For the purposes of the current study, two related questions are posed: (a) what are the associations between specific risk factors, risk assessment tools, and criminogenic outcomes, and (b) what are probation officers' perceptions regarding risk management tools? The findings of the present study will provide researchers and practitioners with a better understanding of the utility of risk assessment in guiding supervision.

METHODS

The current study addressed the research questions through an explanatory sequential mixed methods design. Specifically, quantitative analysis was performed with the goal of analyzing the relationships between risk factors, the PCRA and RPI, and criminogenic outcomes. Subsequently, qualitative analysis was completed to clarify and expand upon the findings made during the quantitative analysis section. Research literature has consistently articulated the utility of completing mixed methods procedures, particularly related to criminological research (Maruna, 2010). Mixed methods designs are useful for data integration and clarity, as well as broadening the feasible range of a research process (Creswell & Creswell, 2017; Greene et al., 1989). For the purposes of the current study, the overarching goal was to supplement quantitative findings with qualitative interviews from practitioners who have acute experience with the subject matter and use of federal risk assessment tools.

Phase I: Quantitative Analysis

Data for this portion of the study were originally gathered as part of a large-scale evaluation of the implementation of a program offered by the federal judicial district of Connecticut, known as the ACT (Achievement/Commitment/Trust) Reentry Court (Myers et al., 2022). The ACT Reentry Court is a program that “offers an intensive alternative to traditional supervision with a focus on encouraging participants to live pro-social, law-abiding lives, and helping participants to stabilize their lives by means of access to community services and benefits” (United States District Court District of Connecticut, 2023). The program aims to help promote these behaviors among eligible federal offenders returning to the community by providing services that have been established as useful in promoting prosocial behaviors, such as job application preparation and assistance with housing opportunities (Bouffard et al., 2000;

Bowman & Ely, 2020; Graffam et al., 2014). The ACT Reentry Court consists of a diverse set of criminal justice-related stakeholders, including the U.S. District Court, the U.S. Attorney's Office, Federal Public Defenders, the U.S. Probation Office, the U.S. Marshal's Office, and various community service providers.

Participation in the program is typically designed to last one year, with required biweekly meetings to go over participant progress. Attendees go through four separate phases that emphasize adjustment, achievement, commitment, and trust (United States District Court for the District of Connecticut, 2018). The ACT Reentry Court is limited to a maximum capacity of 20 justice-involved individuals at any given time. Admission criteria for the program include individuals under federal supervision, voluntary participation, notice to the sentencing judge, and prior eligibility for moderate- or high-risk supervision. The ACT Reentry Court excludes from participation those who suffer from serious substance abuse addiction or certain severe psychological disorders (e.g., pyromania, schizophrenia, pedophilia, etc.), as well as those convicted of certain sex offenses. Data for the previous evaluation project were collected from the spring through the summer of 2022 (Myers et al., 2022).

Measures

Criminogenic Outcomes. The current study measured criminogenic outcomes using three overarching variables, the first of which is recidivism. Although recidivism as an outcome measure was previously critiqued in this paper, it serves two practical purposes for the current study. First, it replicates the use of this measure to provide an adequate comparison to previous studies similar in design and scope. Second, it was not the sole subject of study for outcome variables, lessening the impact of its limitations mentioned above and providing useful indicators related to other variable groupings. The second outcome evaluated in the current study was probation revocation. Probation revocation differs from rearrest in that it deals with the discretion of judges and probation officers as to whether a client should be removed from supervision. The rationale for such decisions is based on several factors and often results from incidents that may not be an “arrestable” offense (i.e., technical violations).

The third outcome variable assessed was drug use, measured by the occurrence of a positive drug test. According to ACT Reentry Court data, participants were required to complete drug tests on a semi-regular basis (United States District Court for the District of Connecticut, 2018). The last outcome variable being measured is program success. Program success originally was coded at the nominal level, including possible outcomes of “graduated,” “left successfully,” “suspended,” “terminated,” or “left unsuccessfully.” “Left successfully” was defined as a participant not graduating but still adhering to prosocial behavior while in the program.

Risk Factor Groupings. Eight total risk factor groupings were used over the course of the examination, the first of which was demographics. Demographics included the variables of race, age, relationship status, education, and employment. Employment was measured at three points during participation in the ACT Reentry Court: at the beginning of the program, during the program, and at the end of participation in the program. The participants' educational attainment was assessed based on their acquisition of a high school diploma or GED, absence of a high school diploma or GED, or attainment of an educational level beyond that of a high school diploma or GED.

The second grouping of risk factors was prior criminal sanctions. The variables in this group consist of previous non-compliance, total offense level and criminal history points from guidelines, and prison time sentence length. The third grouping included prior incidents of criminal behavior, officially known as criminal patterns and violence (CPV). The CPV consists of variables initially measured dichotomously in the Probation and Pretrial Services Automated Case Tracking System (PACTS) and subsequently combined into an additive index. The variables included in the CPV composite score are previous criminal activity under supervision, patterns of similar criminal activity, criminal associations, evidence of prior weapon charges, other violent incidents, institutional adjustment problems, domestic violence, gang involvement, and any pending charges. A higher score indicates the presence of more of these variables. The fourth grouping of risk factors includes drug-related variables. It consists of variables measuring prior drug charges, the age at which drug use first began, prior hard drug use, and previous substance abuse treatment (SAT). The SAT score is a composite measure of past and present substance abuse treatment-related variables, including outpatient, inpatient, self-help, and confined treatment.

The last three groupings of variables are habitation, mental and physical health, and existing protective factors. Habitation includes the number of addresses recorded for program participants throughout ACT reentry court as well as which court location the participant experienced (New Haven, Bridgeport, or Hartford). The next grouping of risk variables includes mental and physical health. The variables that fall under this grouping are whether a participant has medical problems, evidence of a mental illness, and the type of treatment they may have received during their tenure at reentry court. The last grouping of variables focuses on existing protective factors. Existing protective factors are recorded in PACTS at the start of supervision. These protective factors are measured dichotomously and include motivation to change, strong social support, a good work history, a reliable source of income, and special work skills. Similar to the CPV total score variable, the composite protective factor score was an additive index that assessed the presence or absence of each individual factor. The total score quantified the overarching relevancy of these protective factors in a client's life.

Risk Assessment Tools. Beginning and ending PCRA scores were recorded for each individual in the dataset. Initial PCRA scores were the focus of the current research, as they provide a more useful temporal-based assessment in association with criminogenic outcomes. Points for the PCRA are tallied, and an overall score is placed into four groupings. Scores of 0 to 5 lead to a “low risk” designation. Scores between 6 and 9 lead to a “low/moderate” risk designation. Scores between 10 and 12 lead to a “moderate” risk designation. Finally, scores of 13 or above lead to a “high risk” designation. As another example of the common spread of risk classification to rearrest ratio identified in studies evaluating the PCRA, Lowenkamp et al. (2015) found that within 24 months of their evaluation study, individuals were rearrested at a rate of 7%, 20%, 36%, and 51% for low, low-moderate, moderate, and high-risk group classifications, respectively. Separately, RPI scores were measured once at the beginning of supervision. RPI scores range from 0 to 9. In a similar vein, a score between 0 and 2 is designated as low risk, a score between 3 and 6 is categorized as medium risk, and a score of 7 to 9 represents a high-risk designation.

Analysis

In order to investigate the first research question, the initial analysis was conducted in a three-step process. IBM SPSS statistical software (version 29) was employed for all steps of the evaluation. The first phase of the analysis began with a rudimentary examination of the variables through gathering and analyzing general descriptives. Specific information regarding frequencies, measures of central tendency (including means, medians, and modes where appropriate), and measures of dispersion (including variance and standard deviation) was generated. Assembling these statistics was an essential first step in data analysis procedures. In particular, recording descriptives is important for ensuring sufficient statistical assumptions (Lewis-Beck, 1995). Two major assumptions related to the acquisition of descriptives include the appropriate spread/diversity of responses and determining the most common responses for each variable (Ho, 2006; Lewis-Beck, 1995). For the current study, this process helped to identify and eliminate variables that were too heavily skewed and, therefore, warranted exclusion from further analysis because of their inability to provide sufficient statistical variability. In essence, conducting univariate analysis functioned as a necessary foundational step in the overall process of investigating the relationships between the variables.

The second stage of the process was completed by performing bivariate analyses. Bivariate analyses are conducted by researchers in order to understand the relationships between two variables (Lewis-Beck, 1995; Sims, 2000). Specifically, they are used in a variety of contexts to magnify understanding of the direction and strength of one variable relative to another. Bivariate analysis was useful for the current study given the research goal of examining and comparing several variables of different respective groupings (i.e., between individual risk factors, criminogenic outcomes, and federal risk assessment results). A variety of statistical techniques for bivariate analysis were used, including chi-square, analysis of variance (ANOVA), t-tests, and bivariate correlations.

The primary test utilized in the current examination was the chi-square test of independence. Chi-square is useful for identifying relationships between variables by matching the relative frequencies and patterns produced in a random sample and calculating whether two categorical-level variables are independent of one another (Franke et al., 2012; Lewis-Beck, 1995; Sims, 2000). In other words, it determines whether a response in one category has any association with a response in another. The computation of whether there is independence is achieved through the application of hypothesis testing, where the null hypothesis assumes that the variables are independent, while the alternative hypothesis assumes that they are not (Lewis-Beck, 1995). In the context of the present study, the chi-square test of independence was deemed most suitable, as a substantial portion of the independent and dependent variables are categorical.

Additionally, t-tests, ANOVAs, and bivariate correlations were used to further examine the associations between different variables in the study. A t-test is a two-population test utilized to examine the differences between the means of two samples (Hinton et al., 2014; Kim, 2015; Park, 2009). This method is employed when the independent variable is dichotomous and the dependent variable is continuous. While t-tests come in three unique forms, an independent two-sample t-test (two-tailed) is most appropriate for the current data. This statistical test is used when there are two separate population means being examined (Hinton et al., 2014; Kim, 2015; Park, 2009). ANOVA is similar to the t-test, but is computed when there are more than two classes in the independent variable, rather than a dichotomy (Braver et al., 2003; Gamst et al., 2008). A point biserial correlation produces an effect size between variables and is an offshoot of Pearson's r correlation coefficient (Kornbrot, 2014; Tate, 1954). Point bi-serial correlations are utilized when there is one continuous variable and one dichotomous variable. All statistical hypothesis tests were followed up with additional measures of association when appropriate. While basic hypothesis tests utilizing chi-square, t-tests, and ANOVA indicate whether there is a statistically significant association between two variables, additional measures such as Cramer's V and Lambda provide valuable assistance to researchers in assessing the magnitude of any perceived relationships (Lewis-Beck, 1995).

It is crucial to acknowledge that the analysis conducted at the bivariate level is not conclusive in itself, as it fails to consider the potential influence of other independent variables on a singular dependent variable. As outlined previously, particularly in the realm of social sciences, it is widely recognized that a multitude of macro and micro factors can exert an impact on individual outcomes and decision-making patterns. Consequently, by incorporating a greater number of independent variables into an analysis involving social phenomena, a more extensive range of variations can be explained. To address the shortcomings in accounting for explained variance, one plausible approach is to engage in multivariate analysis.

Multivariate analysis was employed to ascertain the degree of association between the individual risk factor variables, federal risk assessment results, and criminogenic outcomes by incorporating multiple covariates at once. Multivariate analysis entails the measurement of the effect of multiple independent variables on a dependent variable in a statistical model (Tabachnick et al., 2013). This process is more efficient than computing each relationship individually. Moreover, this methodology allows for a more robust and comprehensive conclusion, as it theoretically accounts for a greater extent of variation in the dependent variable being examined. There are a variety of approaches to multivariate data analysis, depending on the type of data and desired results.

The current study used a mix of binomial logistic regression techniques for the evaluation. Logistic regression produces the probability of specified outcomes based on different combinations of independent variables (Menard, 2002). The natural logarithm of the odds (log-odds ratio) is used to interpret this process and is expressed by the following formula (Menard, 2002):

$$\text{logit}(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_K X_K$$

Wherein “logit(Y)” is equivalent to the total odds a subject falls under one classification of the dependent variable, “α” is the intercept, “β” is the slope, and “X” denotes the applicable estimate for an independent variable in the equation. Binary logistic regression is used when the dependent variable is dichotomous, and multinomial logistic regression is used when the dependent variable is nominal with multiple categories (Menard, 2002).

Initially, all variables were thoroughly investigated to ensure proper statistical assumptions were met, including independence of observations and satisfactory collinearity (Menard, 2002; Stoltzfus, 2011). Once this process was completed, calculations were made based on the predetermined value categories (e.g., basic demographics, prior criminal sanctions, criminal patterns and violence, etc.). Following this progression, the variables exhibiting the most pronounced log-odds ratio were cross-referenced with those from other groupings. This exploratory process revealed what independent variables most strongly predicted the odds of the dependent variables’ outcome. Finally, stepwise logistic regression with forward insertion was utilized to statistically identify the most significant predictors of the behavioral outcomes. In summary, this procedure served the purpose of helping to disentangle the strengths of the relationships between specific risk factor variables, federal risk assessment results, and diverse criminogenic outcomes.

Phase II: Qualitative Analysis

Semi-structured interviews were conducted with federal probation officers working in Probation and Pretrial Services in the U.S. District of Connecticut. Questions included general inquiries regarding officers’ perceptions of instrument accuracy and functionality, as well as any possible criticisms. Probation officers were selected based on their experience working with clients involved in the ACT Reentry Court and post-conviction supervision more generally. As mentioned previously, there were three main locations where probation officers and their clients participated in the reentry program. These three locations include the cities of Hartford, Bridgeport, and New Haven. Attempts were made to perform the interviews in any way appropriate to maximize participation (i.e., via Zoom, over the phone, or in person). Approval to conduct these interviews was obtained through the University of New Haven's Institutional Review Board (IRB) protocol #2023-082. Participants were informed that their participation was voluntary and that any response given would not contain personally identifiable information.

Analysis

The present study included a systematic procedure for qualitative data analysis. The principal mode of this phase of the investigation incorporated general content and thematic analysis through response deconstruction. Thematic analysis was the focus of the study given its flexibility in data analysis and its ability to determine emerging patterns in the data (Guest et al., 2011; Terry et al., 2017). In particular, an experiential thematic framework was appropriate for the current study. This construct is concerned with capturing how individuals experience the world around them (Braun & Clarke, 2013). Once objectives were outlined and notes from interviews were compiled, a standardized six-step process of thematic analysis was followed, as originally outlined in Terry et al. (2017). This procedure involves data acclimation, code generation, initial theme development, theme review, theme refinement, and producing final reports. Collectively, an experiential thematic analysis recognizes the inherent value produced by gathering information from others, in this case federal probation officers, and what their perspectives may add to the practice of risk assessment.

RESULTS

The following section details the results of the phases of statistical analysis employed to address the questions related to the interrelationships among diverse risk factors, risk assessment tools, and criminogenic outcomes. Furthermore, the second half of the section will elucidate the perceptions of federal probation officers in these contexts. First, the results of the univariate analysis will be presented, which provide a base understanding of the variables in the study. Following this description, results of the bivariate analysis will be provided. A series of tables and explanations will summarize the bivariate tests, to include chi-square, t-tests, correlations, and ANOVA. Subsequently, a series of multivariate logistic regression models will be presented to better understand what variables are best at predicting each of the outcomes of the study. Finally, the results of several semi-structured interviews will be presented to combine with the quantitative findings, providing contextual themes surrounding the opinions of federal probation officers regarding risk assessment instruments. In all, the presentation and dissemination of these results will provide useful implications for the future consideration of risk factors and risk assessment tools.

Phase I: Quantitative Analysis

Descriptive Statistics

In terms of the risk assessment tools, a total of 114 participant risk scores were recorded for the PCRA, and 87 risk scores for the RPI were contained in the current sample. As depicted in Table 1, the number of individuals for each PCRA risk categorization included 3.2% identifying as low risk (n = 3), 32.5% identifying as low/moderate risk (n = 37), 56.1% identifying as moderate risk (n = 64), and 8.8% identifying as high risk (n = 10). Notably, the spread in risk classification, and particularly the higher percentages of the sample categorized as either low/moderate or moderate, is important to consider when attempting to examine the validity of the PCRA as an accurate tool. Concerning the RPI, 6.9% of the sample scored between 0-2 (n = 6), 74.7% of the sample scored between 3-6 (n = 65), and 18.4% scored between 7-9 (n = 16). Overall, the data indicates that most participants fell around a moderate designation of risk under the RPI.

Table 1

Post-Conviction Risk Assessment (PCRA) and RPI Scores Across Sample

Risk Scores	n	%	Mean	SD
PCRA (N = 114)				
Low (0-5 points)	3	3.2		
Low-Moderate (6-9 points)	37	32.5		
Moderate (10-12 points)	64	56.1		
High (13-21 points)	10	8.8		
RPI (N = 87)			5.02	1.88

Table 2 provides a comprehensive overview of the first group of variable descriptive statistics for the sample, which includes basic demographics. As demonstrated in Table 2, a majority of the racial/ethnic makeup of the sample consisted of Blacks/African Americans (71.7%, n = 86), while 15.9% included White and Black Hispanics (n = 18), and only around 8.3% of the sample was identified as White/Caucasian (n = 10). A majority of participants were involved in some type of marital or cohabitating relationship (75.4%, n = 86). In terms of education, the sample was slightly weighted toward those who had received a high school diploma or GED (57.9%, n = 66) as opposed to those who did not (42.1%, n = 48). Although a large percentage of individuals were not employed at the beginning of Reentry Court (69.3%, n = 70), 85.1% were able to be gainfully employed during the program (n = 97). Finally, the average age for a participant at the beginning of Reentry Court was 40 years (*SD* = 8.57).

Table 2

Descriptive statistics for Group 1: Basic Demographics (N = 114)

Variables	n	%	Mean	SD
Race				
Caucasian	10	8.30		
White Hispanic	16	13.3		
African American	86	71.7		
Black Hispanic	2	1.7		
Relationship Status				
Single	28	24.6		
Married or Cohabitating	86	75.4		
Education				
HS Diploma or GED	66	57.9		
No HS Diploma or GED	48	42.1		
Employed at Start				
Yes	35	30.7		
No	79	69.3		
Employed During				
Yes	97	85.1		
No	17	14.9		
Age at Start of Reentry Court			39.99	8.57

Table 3 contains information regarding a second group of variables, which includes measures related to prior criminal sanctions. Approximately 72% of the sample had no prior history of non-compliance during their supervision (n = 82). Additionally, the total offense level from federal sentencing guidelines was typically around 28 (SD = 8.7), while the number of criminal history points from the guidelines was closer to 11 (SD = 6.7). In general, the higher the scores on either or both of these scales, the more time a defendant will spend in federal prison. On average, the current sample had spent about 132 months, or 11 years, incarcerated. This number is just under the average length of federal imprisonment, which amounts to 145 months as reported by the U.S. Sentencing Commission (United States Sentencing Commission, 2023).

Table 3

Descriptive Statistics of Group 2: Prior Criminal Sanctions (N = 114)

Variables	n	%	Mean	SD
Pre-Reentry Court Non-Compliance				
Yes	32	28.1		
No	82	71.9		
Total Offense Level from Guidelines			27.76	8.73
Criminal History Points from Guidelines			10.77	6.73
Prison Time Sentence Length			132.54	106.82

In Table 4, a third grouping of variables includes information regarding criminal patterns and violence (CPV). Within the sample, there were a limited number of individuals who had pending charges (4.4%, n = 5), were involved in gang activity (12.3%, n = 14), had a previous history of domestic violence (16.7%, n = 19), or experienced difficulties adjusting to incarceration (19.3%, n = 22). A larger percentage of individuals had committed other prior violence (28.1%, n = 32), had prior weapons charges (26.3%, n = 30), and reported affiliating with other criminal associates (29.8%, n = 34). The variables within the CPV that had the largest percentage of individual involvement were evidence of a pattern of similar activity contained in criminal records (49.1%, 56) and engagement in any form of criminal activity while on supervision (40.6%, n = 46). Finally, the average total CPV score per individual in the sample, which added the dichotomous CPV variables into a single continuous measure, was 2.26 with a standard deviation of 2.09. This means that individuals in the sample generally exhibited two or more of the 10 characteristics contained within the CPV variables, with some positive skew in the distribution.

Table 4

Descriptive Statistics of Group 3: Criminal Patterns and Violence

Variables	n	Percent Total	Mean	SD
Criminal Activity on Supervision				
Yes	46	40.6		
No	68	59.4		
Pattern of Similar Criminal Activity				
Yes	56	49.1		
No	58	50.9		
Criminal Associations				
Yes	34	29.8		
No	80	70.2		
Prior Weapon Charges				
Yes	30	26.3		
No	84	73.7		
Other Violence				
Yes	32	28.1		
No	82	71.9		
Institutional Adjustment problems				
Yes	22	19.3		
No	92	80.7		
Domestic Violence				
Yes	19	16.7		
No	95	83.3		
Gang Involvement				
Yes	14	12.3		
No	100	87.7		
Pending Charges				
Yes	5	4.4		
No	109	95.6		
CPV Total			2.26	2.09

In terms of substance abuse-related factors (see Table 5), around 70% of the total sample had been convicted of some type of drug charge (n = 80). In addition, 57% reported prior hard drug use, which was defined as the use of any drug not including alcohol or cannabinoids (n = 65). The average age at which drug use began within the current sample was about 14 years old (SD = 2.96). Lastly, the mean SAT score for participants, which was calculated by totaling individual treatment factors, was 1.37 (SD = .998). These results generally indicate that, although the U.S. District of Connecticut has a separate program (known as Support Court) in place for federal offenders who have been incarcerated and have substance abuse addictions, many of the individuals involved in Reentry Court had exposure to illegal substance use and treatment experiences.

Table 5

Descriptive Statistics of Group 4: Drug-Related Factors

Variables	n	Percent Total	Mean	SD
Convicted of a Drug Charge				
Yes	80	70.2		
No	34	29.8		
Prior Hard Drug Use				
Yes	65	57.0		
No	49	43.0		
SAT Total Score			1.37	1.00
Age Drug Use Began			13.82	2.96

As shown in Table 6, the sample was split disproportionately between the three different court locations. A total of 23.7% of participants went to the program in the city of Bridgeport (n = 27). Meanwhile, 28.1% went to Reentry Court in Hartford (n = 32), and the remainder participated in Reentry Court in the city of New Haven (48.2%, n = 55). In terms of addresses, participants had a mean of 2.58 total addresses before they participated in Reentry Court (SD = 1.7), a mean of 1.97 addresses after their participation ended in Reentry Court (SD = 1.4), and a total average of 4.55 addresses recorded in PACTS (SD = 2.3).

Table 6

Descriptive Statistics for Group 5: Habitation and Court Location

Variables	n	Percent Total	Mean	SD
Court Location				
Bridgeport	27	23.7		
Hartford	32	28.1		
New Haven	55	48.2		
Number of Prior Addresses Pre-Reentry Court			2.58	1.74
Number of Addresses Post Reentry Court			1.97	1.37
Total Addresses			4.55	2.27

Table 7 includes variables related to mental and physical health, showcasing a number of results. First, only 24.6% of the sample was recorded as having a diagnosed medical issue or disorder (n = 28). However, 64.9% had some evidence of a mental disorder (n = 74). There were four basic options for Reentry Court treatment recorded in the data. The first of these was that the participant received no treatment. A total of 19 individuals received no treatment, totaling 16.7% of the sample. The second option, substance abuse treatment, was implemented for 34.2% of the total sample (n = 39). The third option included mental health treatment. There were 22 participants in the sample recorded as receiving mental health treatment, which represented 19.3% of the sample. The final option was that a participant receive both substance abuse and mental health treatment. According to the results, 29.8% of the total sample fell into this category (n = 34). Overall, a majority of individuals received some type of treatment during supervision.

Table 7

Descriptive Statistics for Group 6: Mental and Physical Health

Variables	n	Percent Total
Medical Issue or Disorder		
Yes	28	24.6
No	86	75.4
Evidence of a Mental Disorder		
Yes	74	64.9
No	40	35.1
Treatment in Reentry Court		
No Treatment	19	16.7
Substance Abuse Treatment	39	34.2
Mental Health Treatment	22	19.3
Both Treatment	34	29.8

The final grouping of variables included information regarding protective factors. Only a small percentage of individuals in the sample were recorded as having a good work history (10.5%, n = 12), a reliable source of adequate income (16.7%, n = 19), or special work skills (12.3%, n = 14). A larger percentage of the sample was recorded as having strong social support (57.9%, n = 66). Finally, the predominant protective factor recorded within the sample was the motivation to enact change, as reported for 66.7% of the participants (n = 76). Interestingly, the average total score for protective factors was 1.64 (SD = 2). This indicates that participants tended to showcase a mix of one to two of the five factors included in the protective factor composite score.

Table 8

Descriptive Statistics for Group 7: Protective Factors

Variables	n	Percent Total	Mean	SD
Motivated to Change				
Yes	76	66.7		
No	38	33.3		
Strong Social Support				
Yes	66	57.9		
No	48	42.1		
Good Work History				
Yes	12	10.5		
No	102	89.5		
Reliable Source of Adequate Income				
Yes	19	16.7		
No	95	83.3		
Special Work Skills				
Yes	14	12.3		
No	100	87.7		
Protective Factor Score Total			1.64	2.01

As presented in Table 9, there were a total of four dependent variables being examined. These variables were employed for the purposes of comparing the current research with past studies evaluating the RPI and PCRA. In previous research, the most commonly utilized outcome variable was rearrest. In total, 31.6% of the individuals in the sample were rearrested during their respective periods of post-conviction supervision (n = 36). Additionally, 18.4% had their probation revoked (n = 21). As a reminder, revocations pertain to situations wherein an individual involved in the justice system has their supervision formally rescinded by a judge or probation officer. This can occur due to criminal or non-criminal behavior that violates their condition of release. Meanwhile, arrests are made by police exclusively based on criminal behavior. Overall, the data demonstrates that the chances of having one's supervision revoked were less likely than being arrested.

Beyond rearrest and revocation, another critical outcome variable analyzed was whether participants failed a drug test during their supervision. In total, approximately 40% of participants in the sample failed a drug test (n = 46). This finding reinforces the idea that many participants struggled with substance use or abuse during their time in Reentry Court. The final dependent variable evaluated was Reentry Court outcome. Apart from the cases that were still active in Reentry Court (14.9%, n = 17), 57% had a satisfactory or successful outcome (n = 65). A satisfactory or successful outcome was defined as a participant formally graduating or leaving the program successfully. A participant left successfully if their involvement with the program ended before they graduated, but they were otherwise successful in the program. For instance, this criterion would apply if their supervision ended or they were transferred to another jurisdiction.

Table 9

Descriptive Statistics for Criminogenic Outcomes

Variables	N	Percent Total
Rearrest		
Yes	36	31.6
No	78	68.4
Post-Conviction Revocation		
Yes	21	18.4
No	93	81.6
Failed Drug Test		
Yes	46	40.4
No	68	59.6
Reentry Court Outcome		
Graduated or Left Successfully	65	57.0
Terminated, Suspended, or Left Unsuccessfully	32	28.1
Active Cases	17	14.9

Bivariate Analysis for Independent and Dependent Variables

Federal Risk Assessment Instruments and Behavioral Outcomes. Two different techniques were utilized for evaluating the bivariate relationships between the two federal risk assessment tools and the four dependent measures. The first of which was the chi-square test of independence. As mentioned previously, a chi-square test was appropriate for many of the variables, given their categorical structure. Regarding the two federal risk tool scores, a chi-square analysis was used for the PCRA and dichotomous dependent variables. In terms of the RPI, a mathematical equivalent to Pearson's correlation coefficient was run to measure the relationship between continuous RPI scores and dichotomous dependent variables. In this particular case, a point bi-serial computation was used to account for these distinct levels of measurement. Overall, it should be noted that many of the tables in the following sections only display limited output data for ease of interpretation. Full tables can be found in Appendix A.

In order to adequately measure PCRA risk scores, it was necessary to condense the groupings due to the limitations in the data for the lowest and highest categories. Therefore, the subsequent analysis is a result of dichotomized PCRA scores, with the low and low-moderate and the moderate and high categories being grouped together, respectively. After conducting a chi-square analysis to examine the relationship between PCRA scores and the behavioral outcomes, statistically significant associations were identified for all four dependent variables. As revealed in Table 10, PCRA and probation revocation showcased the strongest relationship, with a phi value of .255 and a p-value of .007. The precise interpretation of phi values' strength remains subject to debate. However, it is fair to assume this number denotes a moderate level of strength in the positive relationship between these two variables. This means that those who are categorized as moderate or high risk are significantly more likely to have their supervision revoked.

Table 10

Chi-Square Tables: PCRA and Revocation

		Low-Low/Mod		Mod-High		Total	
		n	%	n	%	n	%
Post-Conviction Revocation	No	38	95.0%	55	74.3%	93	81.6%
	Yes	2	5.0%	19	25.7%	21	18.4%
Total		40	100.0%	74	100.0%	114	100.0%

a. The relationship between these variables was significant, $\chi2$ (1, n = 114) = 7.386, p = .007, φ = .255

Tables 11-13 present the results of the chi-square test of independence between the PCRA scores and the other three outcome variables. The second strongest association identified between the PCRA scores and behavioral outcomes was for rearrest, with a slightly lower phi value of .223 and a *p*-value of .017. Therefore, those who were deemed to be higher risk by the PCRA were significantly more likely to be rearrested during supervision. Drug use and court outcome were both statistically significant but had slightly weaker associations with PCRA categorization scores. Specifically, the chi-square test performed to examine the relationship between PCRA scores and drug use had a phi value of .193 and a *p*-value of .040. This result indicates that those who scored higher on the PCRA also had a higher chance of failing a drug test during the supervision process.

Lastly, the phi value and *p*-value produced by the chi-square test of independence for reentry court outcome were .215 and .032, respectively. To reiterate, reentry court outcomes were coded either as 0 being a failure or 1 being a success. Therefore, the phi value and percentages shown in Table 13 indicate that being placed into the moderate or high categories significantly decreased the likelihood of reentry court success. In all, these findings are in alignment with research expectations, given the purported ability of the PCRA to adequately predict future risk of recidivism.

Table 11

Chi-Square Tables: PCRA and Rearrest

		Low-Low/Mod		Mod-High		Total	
		n	%	n	%	n	%
Rearrest during or after reentry court	No	33	82.5%	45	60.8%	78	68.4%
	Yes	7	17.5%	29	39.2%	36	31.6%
Total		40	100.0%	74	100.0%	114	100.0%

a. The relationship between these variables was significant, $\chi 2$ (1, n = 114) = 5.653, p = .017, φ = .223

Table 12

Chi-Square Tables: PCRA and Drug Use

		Low-Low/Mod		Mod-High		Total	
		n	%	n	%	n	%
Participant failed drug test during or after	No	29	72.5%	39	52.7%	68	59.6%
	Yes	11	27.5%	35	47.3%	46	40.4%
Total		40	100.0%	74	100.0%	114	100.0%

a. The relationship between these variables was significant, $\chi 2$ (1, n = 114) = 4.228, p = .040, φ = .193

Table 13

Chi-Square Tables: PCRA and Reentry Court Outcome

		Low-Low/Mod		Mod-High		Total	
		n	%	n	%	n	%
Reentry court outcome without active cases	Failure	8	21.6%	27	42.9%	35	35.0%
	Success	29	78.4%	36	57.1%	65	65.0%
Total		37	100.0%	63	100.0%	100	100.0%

a. The relationship between these variables was significant, $\chi 2$ (1, n = 100) = 4.620, p = .032, φ = .215

As shown in Table 14, the point-biserial correlation coefficient calculated to assess the relationship between the RPI and rearrest was found to be significant. Specifically, there was a moderate and positive association between RPI score and rearrest (r = .299, p <.01). This means that those with a higher RPI score were more likely to be rearrested during supervision. However, the point-biserial correlation coefficient calculated to assess the relationship between RPI scores and revocation was not found to be significant, and the point-biserial correlation between RPI scores and drug use was also insignificant. Finally, the point-biserial correlation between RPI scores and court outcome was found to be statistically significant. A moderately strong and negative correlation existed between these two variables (r = -.398, p <.01). Therefore, as an individual's score on the RPI increased, their chances of successfully completing Reentry Court decreased.

Table 14

RPI Point-Biserial Correlational Analysis

Variables		Rearrest	Revocation	Drug Use	Court Outcome
RPI Score	Pearson Correlation	**.299****	.165	.188	**-.398****
	Sig. (2-tailed)	.005	.127	.080	<.001
	n	87	87	87	75

**p ≤ .01; *p ≤ .05

Risk Factors and Risk Assessment Tools. Similar statistical processes were undertaken to better understand the relationship between the various risk factors recorded and the federal risk assessment instruments. Specifically, bivariate correlations, chi-square, t-tests, and ANOVA were used when appropriate and depending on the level of measurement for each variable. Table 15 presents results from the continuous risk factors and both the dichotomous PCRA categorizations and continuous RPI scores. The results showcase that many of the continuous risk factor variables examined in the current study have an association with both the PCRA and RPI scores. This is not surprising, given that many components within these risk instruments include similar or exact measures addressing these factors. Furthermore, the direction of the statistically significant correlations aligns with what was expected, depending on the particular risk factor. For example, age has a statistically significant and negative relationship with both PCRA and RPI scores. This means that the older the individual, the less likely they are to be medium or higher-risk in both instruments. This finding aligns with prior research that indicates a tendency for individuals to "age out" of criminal behavior as they advance through the life course (e.g., Laub & Sampson, 2001). In addition, the total protective factor score had a significant and negative relationship with risk scores. This means the more protective factors an individual may indicate having, the lower their score would tend to be on the federal risk assessment instruments being examined.

With respect to sentencing initiatives, total offense level from guidelines, criminal history points from guidelines, and length of sentence were all associated with both the RPI and PCRA. The higher the offense level one received from sentencing guidelines, the less likely they were to score high on either the PCRA or RPI. Similarly, the longer the sentence imposed on an offender, the less likely they were to be labeled high-risk by either of these risk assessment tools. On the contrary, the lengthier the criminal history one had, the more likely they were to be deemed higher risk according to the PCRA and RPI. These differences reveal that the PCRA and RPI value past criminal history as a strong indicator of future risk, as opposed to the seriousness of the crime according to sentencing guidelines. This may be especially the case for the PCRA, which also had a positive and statistically meaningful relationship with the CPV, a construct primarily concerned with pre-existing criminal conduct.

Noticeably, both the PCRA and RPI lack an association with information regarding addresses. This observation reflects the absence of specifically tailored measurements relating to housing instability within these instruments. Another evident finding is that when comparing the strengths of association between the continuous risk factors and risk instruments, the relationships seem to be a bit stronger between the risk factors and the RPI. This is likely a result of the RPI's predominantly static framework, designed with explicit actuarial factors that are not subject to change, unlike the PCRA. A final result of the bivariate correlational analysis of note is the statistical association between drug-related factors and the federal risk assessment tools. Indeed, there were correlations between SAT score and age drug use began with the RPI, but not with the PCRA. This finding indicates that certain measures of the RPI may capture drug-related factors better than the PCRA.

Table 15

Bivariate Correlational Analysis Risk Factors and Risk Assessment Tools

Variables	PCRA	RPI
Age	**-.240***	**-.339****
Total offense level from guidelines	**-.308****	**-.384****
Criminal history points from guidelines	**.258****	**.378****
Prison time sentence length	**-.354****	**-.402****
Total CPV score	**.243****	.099
SAT score	.106	**.347****
Age drug use began	-.149	**-.261***
Number of addresses prior to reentry court	.108	.016
Number of addresses post reentry court	.093	-.009
Total Addresses	.139	.006
Total protective factor score	**-.335****	**-.335****

**p ≤ .01; *p ≤ .05

In terms of the categorical risk factors and the PCRA, a number of findings emerged. As outlined in Table 16, several risk factors were found to be statistically associated with the PCRA. The strongest association was between a measure of the CPV, prior weapon charges, with a phi of .314. This means that those who had prior weapons charges were more likely to be labeled as medium or higher risk. Two additional CPV measures were also found to be statistically associated with PCRA risk grading. These were any type of criminal activity during supervision and evidence of patterns of similar criminal activity. Both of these outcomes have comparable implications as prior weapons charges, in that an indication of the presence of either of these two components increases the chances that someone from the sample also had a higher PCRA score. Another group of variables statistically related to PCRA scores consisted of some of the protective factors. This included motivation to change, strong social support, and a reliable source of adequate income. The strongest relationship out of these three was strong social support, with $\chi 2$ (1, n = 114) = 9.716, $p = .002$, and $\varphi = .292$. The phi values and percentages in Table 16 indicate that those who were lacking in these particular protective factors were more likely to be designated as medium or higher risk on the PCRA.

Table 16

Chi-Square Crosstabs – General Risk Factors & PCRA

Factors		Low-Low/mod		Mod-High		Total		X^2	φ
		n	%	n	%	n	%		
Criminal Activity on Supervision	No	30	44.1%	38	55.9%	68	100.00%	**6.033***	.230
	Yes	10	21.7%	36	78.3%	46	100.00%		
Pattern of Similar Criminal Activity	No	26	44.8%	32	55.2%	58	100.00%	**4.918***	.208
	Yes	14	25.0%	42	75.0%	56	100.00%		
Prior Weapon Charges	No	37	44.0%	47	56.0%	84	100.00%	**11.251****	.314
	Yes	3	10.0%	27	90.0%	30	100.00%		
Prior Hard Drug Use	No	23	46.9%	26	53.1%	49	100.00%	**5.299***	.216
	Yes	17	26.2%	48	73.8%	65	100.00%		
Evidence of a Mental Disorder	No	8	20.0%	32	80.0%	40	100.00%	**6.159***	.232
	Yes	32	43.2%	42	56.8%	74	100.00%		
Motivated to Change	No	8	21.1%	30	78.9%	38	100.00%	**4.930***	.208
	Yes	32	42.1%	44	57.9%	76	100.00%		
Strong Social Support	No	9	18.8%	39	81.3%	48	100.00%	**9.716****	.292
	Yes	31	47.0%	35	53.0%	66	100.00%		
Reliable Source of Adequate Income	No	29	30.5%	66	69.5%	95	100.00%	**5.207***	.214
	Yes	11	57.9%	8	42.1%	19	100.00%		

**$p \leq .01$; *$p \leq .05$

In reference to the RPI, both t-tests and ANOVA were completed for the categorical risk factors. There were fewer statistically significant associations identified compared to the PCRA. Of the three variables explored using ANOVA, race/ethnicity, court location, and treatment in Reentry Court, none were found to be statistically significant. A full table of ANOVA results can be found in Appendix A (Table A3). Furthermore, as shown in Table 17, only three variables explored using t-tests were identified as statistically meaningful. These variables included employment during Reentry Court, motivation to change, and strong social support. Those who were employed while in Reentry Court tended to have lower scores on the RPI. In addition, individuals in the sample who had a recorded motivation to change and strong social support scored lower on the RPI. In terms of effect sizes, all significantly associated variables can be interpreted as having a medium to strong association with the RPI, with a Cohen's d of .416, .670, and .809, respectively (Gignac & Szodorai, 2016). A full table of results from t-tests can be found in Appendix A (Table A2).

Table 17

T-Test for Risk Factors and RPI

Factors		n	M	SD	$t(85)$	Cohen's d
Employment During	No	15	5.67	1.113	**1.467***	.416
	Yes	72	4.89	1.983		
Motivated to Change	No	29	5.83	1.891	**2.946****	.670
	Yes	58	4.62	1.755		
Strong Social Support	No	37	5.84	1.803	**3.730****	.809
	Yes	50	4.42	1.715		

$^{**}p \leq .01$; $^{*}p \leq .05$

Risk Factors and Behavioral Outcomes. The final step undertaken for the bivariate stage of quantitative analysis was the assessment of the relationships between the risk factors and the four behavioral outcomes. The main purpose of this approach was to ascertain and compare different statistically meaningful correlations across the three broad categories of risk factors, risk assessment scores, and behavioral outcomes. Similar to previous analyses, bivariate correlations and chi-square tests were used depending on the nature of the variables examined. Table 18 includes the bivariate correlations explored, while Tables 19-22 contain the chi-square and cross-tabs generated.

Many continuous risk factors shared statistically significant relationships with the dependent behavioral outcome variables (see Table 18). Age, total offense level from sentencing guidelines, and prison sentence length were statistically related to all four outcome variables. Regarding age, the older an individual was, the less likely they were to be rearrested, have their supervision revoked, fail a drug test, or fail Reentry Court. This pattern also applies to the total offense level received according to federal guidelines. This does not come as a surprise, considering that the higher the offense level, the more years one will spend in a federal prison and the older an individual will be once they are released.

Though the number of addresses prior to Reentry Court was not statistically significant, both the number of addresses after Reentry Court and the total number of addresses displayed statistical significance with rearrest and court outcome. The total number of addresses was also significantly related to supervision revocations. The direction of these relationships is in line with research expectations, as they both had positive relationships with rearrest and negative relationships with court outcomes. In other words, the more addresses someone had, the more likely they were to be rearrested and the less likely they were to complete Reentry Court successfully.

Table 18

Bivariate Correlations Analysis: Risk Factors and Behavioral Outcomes

Variables	Rearrest	Revocation	Drug Use	Court outcome
Age	**-.184***	**-.287****	**-.269****	**.395****
Total offense level from guidelines	**-.261****	**-.276****	**-.331****	**.336****
Criminal history points from guidelines	.099	-.004	-.145	.121
Prison time sentence length	**-.233***	**-.274****	**-.390****	**.399****
Total CPV score	.014	.038	-.001	-.023
SAT score	.090	.052	**.199***	-.027
Age drug use began	-.146	-.004	**-.272****	.143
Number of addresses prior to reentry court	.024	.129	-.130	-.161
Number of addresses post reentry court	**.275****	.224	.186	**-.225***
Total Addresses	**.185***	**.234***	.012	**-.260****
Total protective factor score	**-.188***	-.167	-.150	**.297****

**p ≤ .01; *p ≤ .05

Another finding of note is that the total protective factor score had statistically significant relationships with rearrest and court outcome, while the total CPV score did not. The observed associations between the total protective factor score and the aforementioned outcomes are in accordance with anticipated results. Specifically, a greater degree of exposure to prosocial factors, as indicated by higher scores on the protective factor scale, is inversely related to the probability of rearrest and positively associated with the successful completion of the Reentry Court program. Meanwhile, the CPV score had one of the fewest correlations out of all the continuous risk factors, exhibiting no statistical significance whatsoever. Lastly, both risk factors associated with substance abuse (SAT score and age at which drug use began) were significantly related to general drug use outcomes. The results demonstrate that the younger individuals were when they began using, and the more drug treatment therapy they received, the more likely they were to engage in substance use while under supervision. These associations are also in line with what one might expect, given that those who have lengthier and more acute addictions to substances are more likely to receive treatments. There is also the possibility that the treatment received may have come after failed drug tests; or, despite the treatment, individuals may be more predisposed toward relapse because of their history of drug use.

Rearrest. Table 19 contains significant factors for rearrest. A full table of results can be found in Appendix A (Table A4). Three categorical risk factors showcased statistical significance with rearrest during supervision. The first was employment during reentry court, $\chi 2$ (1, n = 114) = 4.220, p = .040, φ = .192. As shown in Table 19, of those who were rearrested during Reentry Court, only 27.8% were employed. Subsequently, it can be concluded that being employed during Reentry Court largely decreases the likelihood of being rearrested. The next risk factor statistically related to rearrest was court location $\chi 2$ (2, n = 114) = 6.988, p = .030, φ =

.248. Among the distinct judicial jurisdictions encompassing Bridgeport, Hartford, and New Haven, each locale exhibited arrest rates of 14.8%, 46.9%, and 30.9%, respectively. This means participants in the Bridgeport Reentry Court were least likely to be rearrested, while those at Hartford were the most likely to be rearrested. The last risk factor statistically related to rearrest was a measure of the protective factor scale, strong social support $\chi2$ (1, n = 114) = 10.242, *p* = .001, φ = .300. The rearrest rate for those who indicated they had strong social support was only 19.7%. Meanwhile, those who did not have strong social support exhibited closer to a 48% arrest rate.

Table 19

Chi-Square Crosstabs – Factors and Rearrest

Factors		No Rearrest		Rearrest		Total		X^2	φ/V
		n	%	n	%	n	%		
Employment During	No	8	47.1%	9	52.9%	17	100.0%	**4.220***	.192
	Yes	70	72.2%	27	27.8%	97	100.0%		
Court Location	Bridgeport	23	85.2%	4	14.8%	27	100.0%	**6.988***	.248
	Hartford	17	53.1%	15	46.9%	32	100.0%		
	New Haven	38	69.1%	17	30.9%	55	100.0%		
Strong Social Support	No	25	52.1%	23	47.9%	48	100.0%	**10.242****	.300
	Yes	53	80.3%	13	19.7%	66	100.0%		

**p ≤ .01; *p ≤ .05

Supervision Revocation. Table 20 contains significant factors for revocation. A full table of results can be found in Appendix A (Table A5). Supervision revocation had the second highest number of statistically significant relationships with the categorical risk factors examined. Similar to rearrest, both employment during Reentry Court $\chi2$ (1, n = 114) = 21.702, *p* = <.001, φ = .436, and evidence of strong social support $\chi2$ (1, n = 114) = 4.140, *p* = .042, φ = .191 were statistically significant. The revocation rates for those employed during Reentry Court compared to those who were not were 11.3% to 58.8%. The group that indicated they had strong social support had their supervision revoked at 12.1% while those who did not had a supervision revocation rate of 27.1%. In addition to these particular factors, pre-Reentry Court non-compliance also had a statistically meaningful relationship to supervision revocation $\chi2$ (1, n = 114) = 7.535, p = .006, φ = .257. Comparatively, only 12.2% of those who were compliant had their supervision revoked, while individuals who exhibited some form of non-compliance had their supervision retracted at a much larger rate of 34.3%. Finally, a measure of the CPV, gang involvement, was also statistically related to supervision revocation $\chi2$ (1, n = 114) = 6.342, p = .012, φ = .236. Though there were only a total of 14 individuals who indicated having gang affiliations, their supervision revocation rate was 42.9%. Ex-offenders in the sample who did not have gang affiliations had their probation revoked at a much smaller rate of 15%.

Table 20

Chi-Square Crosstabs – Factors and Revocation

Factors		No Revocation		Revocation		Total		X^2	φ
		n	%	n	%	n	%		
Employment During	No	7	41.2%	10	58.8%	17	100.0%	**21.702****	.436
	Yes	86	88.7%	11	11.3%	97	100.0%		
Pre Reentry Court Non-Compliance	No	72	87.8%	10	12.2%	82	100.0%	**7.535***	.257
	Yes	21	65.6%	11	34.4%	32	100.0%		
Gang Involvement	No	85	85.0%	15	15.0%	100	100.0%	**6.342***	.236
	Yes	8	57.1%	6	42.9%	14	100.0%		
Strong Social Support	No	35	72.9%	13	27.1%	48	100.0%	**4.140***	.191
	Yes	58	87.9%	8	12.1%	66	100.0%		

**$p \le .01$; *$p \le .05$

Drug Use. Table 21 contains significant factors for drug use. A full table of results can be found in Appendix A (Table A6). Drug test outcomes had the fewest statistically valid relationships with the risk factors investigated. Only employment at the start of Reentry Court $\chi2$ (1, n = 114) = 4.495, p = .034, φ = .199, and pre-Reentry Court non-compliance demonstrated a clear statistical association $\chi 2$ (1, n = 114) = 4.672, p = .031, φ = .202. The percentage of individuals who were both unemployed at the beginning of Reentry Court and had a positive drug test was 46.8%, while those who had gainful employment at that time had a positive drug test percentage of 25.7%. For pre-Reentry Court non-compliance, 56.3% of those who exhibited non-compliant behaviors failed a drug test during supervision. Meanwhile, only 34.1% of those who were compliant prior to Reentry Court failed a drug test.

It is also worth noting that two measures relevant to substance use, whether individuals were convicted of a drug charge, and prior hard drug use did not display statistical significance. Despite this finding, in the case of whether individuals were convicted of a drug charge, a larger percentage of those who faced this penalty ended up failing a drug test during supervision compared to those who did not (42.5% failure rate to 35.3% failure rate). However, it was observed that individuals who had previously used hard drugs had a slightly lower failure rate (38.5%) in drug tests compared to those who had never used hard drugs (42.9%).

Table 21

Chi-Square Crosstabs – Factors and Drug Use

Factors		Negative		Positive		Total		X^2	φ
		n	%	n	%	n	%		
Employment at Start	No	42	53.2%	37	46.8%	79	100.0%	**4.495***	.199
	Yes	26	74.3%	9	25.7%	35	100.0%		
Pre Reentry Court Non-Compliance	No	54	65.9%	28	34.1%	82	100.0%	**4.672***	.202
	Yes	14	43.8%	18	56.3%	32	100.0%		
Convicted of a Drug Charge	No	22	64.7%	12	35.3%	34	100.0%	.515	.067
	Yes	46	57.5%	34	42.5%	80	100.0%		
Prior Hard Drug Use	No	28	57.1%	21	42.9%	49	100.0%	.224	.044
	Yes	40	61.5%	25	38.5%	65	100.0%		

**p ≤ .01; *p ≤ .05

Court Outcome. Table 22 contains significant factors for Reentry Court outcomes. A full table of results can be found in Appendix A (Table A7). Whether a participant successfully completed Reentry Court had the largest number of statistically relevant relationships with the risk factor data. In total, five factors reached statistical significance. Similar to other behavioral outcomes, employment during Reentry Court $\chi2$ (1, n = 100) = 23.953, p = <.001, φ = .489, pre-Reentry Court non-compliance $\chi2$ (1, n = 100) = 6.462, p = .011, φ = .254, and the presence of strong social support $\chi2$ (1, n = 100) = 8.974, p = .003, φ = .300 were all statistically associated with the participant's success in the program and were in line with research expectations. Those who were employed, compliant in their behavior prior to Reentry Court, and had strong social support were more likely to succeed in the program.

Two additional relevant factors that had not shown statistical significance with other outcomes were relationship status $\chi2$ (1, n = 100) = 6.330, p = .012, φ = .252 and education $\chi2$ (1, n = 100) = 5.594, p = .018, φ = .237. Those who indicated they were not currently in a relationship had a lower likelihood of success in the Reentry Court program. Those who were single had a success rate of 58.4% while those who were in a relationship had a success rate of 87%. In terms of education, 75% of those who received a high school diploma or GED had a successful court outcome. A smaller 52.3% of participants in Reentry Court without a high school diploma or GED secured a successful outcome.

Table 22

Chi-Square Crosstabs – Factors and Court Outcome

Factors		Failure		Success		Total		X^2	φ
		n	%	n	%	n	%		
Single	No	3	13.0%	20	87.0%	23	100.0%	**6.330***	.252
	Yes	32	41.6%	45	58.4%	77	100.0%		
High School Diploma Or GED	No	21	47.7%	23	52.3%	44	100.0%	**5.594***	.237
	Yes	14	25.0%	42	75.0%	56	100.0%		
Employment During	No	13	92.9%	1	7.1%	14	100.0%	**23.953****	.489
	Yes	22	25.6%	64	74.4%	86	100.0%		
Pre Reentry Court Non-Compliance	No	21	28.0%	54	72.0%	75	100.0%	**6.462***	.254
	Yes	14	56.0%	11	44.0%	25	100.0%		
Strong Social Support	No	21	52.5%	19	47.5%	40	100.0%	**8.974****	.300
	Yes	14	23.3%	46	76.7%	60	100.0%		

**$p \leq .01$; *$p \leq .05$

Multivariate Analysis

Though univariate and bivariate analyses are valuable for shedding light on the data and associations between the variables at hand, they are also limited in their statistical ability to assess relationships while also controlling for other confounding factors. Multivariate analysis mitigates this issue by simultaneously incorporating the influence of multiple variables on an outcome. Consequently, this analytical approach is particularly advantageous in studies like the current research, which aims to examine the collective impact of multiple risk factor variables on the behavioral outcomes of rearrest, revocation, drug use, and court program success. Binary logistic regression emerged as the most suitable procedure for multivariate analysis, due to its ability to assess dichotomous dependent variables.

An exploratory multi-step process was undertaken to employ a rigorous statistical approach that sought to further investigate the relationships between the three broad classifications of variables in the current study. The issue of multicollinearity was addressed through both the evaluation of correlation coefficients in a correlation matrix as well as variance inflation factors (VIF). The two largest correlation coefficients for independent variables included in the current study were .603 and .489, both of which fall below the customary threshold that would typically give rise to multicollinearity concerns. Indeed, $|r| > .7$ is commonly understood as the marker for consideration of possible issues related to multicollinearity (Dormann et al., 2012). Meanwhile, the highest VIF for the independent variables presented in final regression models was 2.130. In general, concerns regarding the potential presence of multicollinearity within a given model arise when the VIF exceeds a threshold of 4.0 (Garson, 2016).

Several regression modeling techniques were utilized, with the ultimate goal of determining which set of variables most effectively predicted the four behavioral outcomes. Models were initially formulated by manually deriving risk factors that generated the most robust associations with the respective outcomes during the bivariate stage of the quantitative analysis. Additional models were developed by computing stepwise logistic regressions using forward insertion and backward elimination techniques. The models presented below are based on stepwise logistic regression with forward insertion of significant independent variables, with supervision time included as a control variable in each final model. These models were chosen based on their parsimonious approach to identifying the most significant predictors of the four dependent variables, while recognizing the issue of small sample size in the dataset.

Table 23

Binary Logistic Regression: Rearrest

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Months of Post-Conviction Supervision	.055	.020	7.761	1	**.005****	1.056
African-American	1.293	.736	3.086	1	.079	3.645
Age at start of court	-.080	.032	6.145	1	**.013***	.923
New Haven Participant	1.098	.728	2.278	1	.131	2.999
Hartford Participant	2.199	.812	7.342	1	**.007****	9.020
# of Addresses Post RC Court	.467	.180	6.701	1	**.010***	1.595
Constant	-3.270	1.799	3.303	1	.069	.038

a. $^{**}p \leq .01$; $^{*}p \leq .05$
b. Pseudo R^2 Values: Cox & Snell = .265, Nagelkerke = .371

A stepwise logistic regression model was estimated to ascertain the effects of individual risk factors and federal risk assessment instrument scores on the likelihood that participants were rearrested. Results are presented in Table 23. The overall forward insertion model was statistically significant, $\chi2(6) = 35.025$, $p < .001$. The model explained 26.5% to 37.1% (Cox & Snell and Nagelkerke R-Squares, respectively) of the variance in the rearrest outcome, and correctly classified 79.8% of cases. A one-unit increase in age at the start of reentry court was associated with a 7.7% decrease in the simple odds of rearrest (OR = .923, 95% CI = 0.87 – 0.98). Members of the reentry court located in the city of Hartford were 9.02 times more likely to be rearrested compared to those participants in the Bridgeport location (OR = 9.02, 95% CI = 1.84 – 44.28). As the number of addresses following Reentry Court initiation went up by one unit, the simple odds of arrest increased by 59.5% (OR = 1.60, 95% CI = 1.12 – 2.27). Lastly, the simple odds of rearrest increased by 5.6% for every one-unit increase in months of post-conviction supervision (OR = 1.06, 95% CI = 1.02 – 1.10)

Table 24

Binary Logistic Regression: Supervision Revocation

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Months of Post-Conviction Supervision	-.021	.026	.627	1	.429	.980
Employment During	-4.222	1.021	17.103	1	**<.001****	.015
Age at start of court	-.143	.046	9.844	1	**.002****	.867
New Haven Participant	3.509	1.374	6.525	1	**.011***	33.413
Hartford Participant	4.334	1.566	7.655	1	**.006****	76.221
Number of Addresses Post Reentry	.664	.211	9.914	1	**.002****	1.942
Constant	2.879	1.775	2.631	1	.105	17.792

a. $^{**}p \leq .01$; $^{*}p \leq .05$
b. Pseudo R^2 Values: Cox & Snell = .339, Nagelkerke = .551

Next, a stepwise logistic regression model was produced to assess the effects of individual risk factors and federal risk assessment instrument scores on the likelihood of supervision revocation for the reentry court participants (see Table 24). The final forward insertion model was statistically significant, $\chi2(6) = 47.259$, $p < .001$, explaining 33.9% to 55.1% (Cox & Snell and Nagelkerke R-Squares, respectively) of the variance in the revocation outcome and correctly classifying 88.6% of cases. Employment during reentry court was significantly and negatively associated with revocation. More specifically, the odds of supervision revocation for those who were employed were about 98% less likely than for those who were not employed during reentry court (OR = .015, 95% CI = .002 – .108). In addition, a one-unit increase in age was associated with a 13.3% decrease in the simple odds of having supervision revoked (OR = .867, 95% CI = .793 – .948). Members of the reentry court located in Hartford were 76.22 times more likely to have their supervision revoked than participants in Bridgeport (OR = 76.22, 95% CI 3.54 – 1641.71), and participants in New Haven were 33.41 times more likely to be revoked compared to Bridgeport participants (OR = 33.41, 95% CI = 2.26 – 493.37). Finally, as the number of addresses following Reentry Court initiation goes up by one unit, the simple odds of supervision revocation increase by 94% (OR = 1.94, 95% CI = 1.285 – 2.94).

Table 25

Binary Logistic Regression: Drug Use

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Months of Post-Conviction Supervision	.007	.017	.144	1	.704	1.007
Employed at Start Date	-1.289	.531	5.904	1	**.015***	.275
Criminal History Points from Guidelines	-.039	.036	1.135	1	.287	.962
Prison Time Sentence Length	-.009	.003	10.198	1	**.001****	.991
Age Drug Use Began	-.199	.099	4.063	1	**.044***	.820
Constant	4.069	1.609	6.394	1	.011	58.512

a. **$p \leq .01$; *$p \leq .05$
b. Pseudo R^2 Values: Cox & Snell = .243, Nagelkerke = .327

A third stepwise logistic regression model was generated to examine the effects of risk factors and federal risk assessment instrument scores on the likelihood that participants failed a drug test. As presented in Table 25, the final model using forward insertion was statistically significant, $\chi2(5) = 30.099$, $p < .001$. The model explained 24.3% to 32.7% (Cox & Snell and Nagelkerke R-Squares, respectively) of the variance in the drug test outcome and correctly classified 71.3% of cases. First, those who were unemployed at the beginning of Reentry Court were 3.63 times more likely to fail a drug test (OR = .275, 95% CI .097 – .779). Additionally, a one-unit increase in sentencing length (measured in months) was associated with a 1% decrease in the simple odds of failing a drug test (OR = .991, 95% CI .985 – .996). Finally, a one-year increase in the age at which drug use began was associated with an 18% decrease in the simple odds of failing a drug test (OR = .820, 95% CI .676 – .995).

Table 26

Binary Logistic Regression: Reentry Court Success

Variables	B	S.E.	Wald	Df	Sig.	Exp(B)
Months of Post-Conviction Supervision	-.001	.024	.002	1	.967	.999
Employed During Reentry Court	5.329	1.521	12.280	1	**<.001****	206.225
Age in Years at Start of Reentry Court	.115	.041	7.729	1	**.005****	1.122
Pre Reentry Court Non-Compliance	-1.462	.682	4.601	1	**.032***	.232
Number of Addresses Post RC Entry	-.593	.229	6.680	1	**.010****	.553
Protective Factor Score	.701	.326	4.626	1	**.031***	2.015
Constant	-7.991	2.494	10.270	1	.001	.000

a. **$p \leq .01$; *$p \leq .05$
b. Pseudo R^2 Values: Cox & Snell = .449, Nagelkerke = .618

A final stepwise logistic regression model (see Table 26) was estimated to assess the effects of individual risk factors and federal risk assessment instrument scores on the likelihood that participants successfully completed Reentry Court. The model using forward insertion was statistically significant, $\chi2(6) = 59.575$, $p < .001$, explaining 44.9% to 61.8% (Cox & Snell and Nagelkerke R-Squares, respectively) of the variance in reentry court success and correctly classifying 81% of cases. Individuals who were employed during reentry court were far more likely to have a successful court outcome (OR = 206.23, 95% CI 10.47 – 4062.45). Furthermore, as age increased by one year, the simple odds of successfully completing reentry court also increased by 12% (OR = 1.12, 95% CI 1.04 – 1.22). Those who did not have a history of court non-compliance were 4.31 times more likely to have a successful reentry court outcome (OR =

.23, 95% CI .06 – .88). In addition, a one-unit increase in the number of addresses following Reentry Court initiation was associated with a 44.7% decrease in the simple odds of a favorable court outcome (OR = .55, 95% CI .35 – .87). Lastly, as the composite protective factor score increased by one unit, the simple odds of graduating or leaving reentry court successfully also increase by over 100% (OR = 2.02, 95% CI 1.06 – 3.82).

Phase II: Qualitative Interviews

This section presents the results of interviews completed with federal probation officers employed by Probation and Pre-Trial Services for the U.S. District of Connecticut. In total, six probation officers were interviewed using a semi-structured technique; two officers were interviewed from each of the three federal court locations in Connecticut. Each interview lasted from 30 to 45 minutes. A list of the interview questions can be found in Appendix B. A mix of deductive and inductive coding was utilized in the process of completing a thematic analysis (Fereday & Muir-Cochrane, 2006). Deductive codes revolved around a general desire to unravel perspectives related to the strengths and weaknesses of the PCRA and RPI. Inductive codes were utilized for building more general contexts surrounding the themes explored in this research. After careful analysis, responses were grouped into four overarching themes: general risk assessment procedures, the RPI, the PCRA, and other challenges tied to risk assessment tools. The overall goal of the interviews was to foster a more comprehensive understanding of the perceptions and contexts surrounding federal risk assessment tools used by probation officers.

General Risk Assessment Processes and Tools

Not surprisingly, a major theme that emerged across all the interviews was the significant emphasis placed upon the Risk-Need-Responsivity (RNR) principles by the federal probation officers. Most of the federal probation officers revealed that a key aspect of their role was to identify the potential risk factors of their clients and to address criminogenic needs through different techniques. In the words of one of the officers, they constantly work to "maximize the potential for success with them [clients]." The officers reported that this framework is critical for guiding the way they effectively and efficiently supervise clients who are added to their respective caseloads. Considerable discussion also revolved around concepts related to the responsivity principle. One example of this was the influence of criminal thinking styles and their impact on the dynamics of supervision.

Furthermore, the federal probation officers consistently alluded to the importance of dissecting and understanding both static and dynamic risk factors when dealing with clients. These elements form the basis on which RNR principles can be applied. Moreover, a majority of the federal probation officers focused more on the importance of dynamic rather than static factors, because, as stated by one of the officers:

> I'm a senior officer and so I get all these highs. I gotta explain why you're high-risk. I say well a big part of your risk score was your criminal history and that you have eight or more arrests. That's three points right there. That's not going to change. You're always going to have three risk points because you're going to have eight or more arrests.

Dynamic risk factors were perceived to be more useful than static ones. That is because they allow for greater capacity to effectuate tangible transformations in the behaviors of clients in a manner that decreases the odds of engaging in future trouble. Indeed, a majority of the most important risk factors identified by the federal probation officers interviewed were dynamic in nature. Examples of those viewed as most essential for identification and targeted change were offender criminal thinking styles, social networks, employment, and substance abuse.

A final common topic evident in the interviews was information gathering. Though not explicitly mentioned in any of the questions asked, it became very apparent that a significant obligation of federal probation officers is to systematically collect and scrutinize data pertaining to their clients. This procedure was generally seen as being most important at the beginning of supervision, so that officers could determine their best course of action moving forward. This understanding ties back to RNR principles and the ability of officers to help address the most pressing issues for their clients. To illustrate, one federal probation officer stated:

> I think, in general, when the information gathering stages begins, so that first meeting with that person, I'm kind of reading their prospective report, getting their social history, what's happened throughout their lives, what they're thinking as they leave and once they've been released. Kind of just gauging with them on what they need to address.

There was also a professed value in continuing the process of collecting information throughout supervision. During the interviews, the officers often alluded to the importance of evidence-gathering and behavioral analysis in their approach to client assistance. Ultimately, this process was more of a requirement than an option for the federal probation officers, due to the complexity and seriousness of the work at hand.

Views on the Risk Prediction Index (RPI)

Much like the lack of past substantive empirical evaluations of the RPI, there was limited opinion from the federal probation officers about the RPI. This was partially due to the department's deprioritization of the RPI over the years. Indeed, due to its gradual discontinuation, more recently hired federal probation officers had no experience with the tool whatsoever. From the scarce opinion offered, much of it was unfavorable. A common belief among those who did have experience using the tool was that it was inferior to the PCRA. One federal probation officer in particular, who had prior experience with more sophisticated risk assessment tools like the LSI-R, likened the use of the RPI to “Like going from using a TI-83 back down to a standard Staples oversized calculator.” Clearly, there was a general sense that the RPI had limited utility, especially compared to other risk assessment tools available. More specifically, according to the officers who had used the RPI, a major flaw was that they were unable to adequately leverage the tool to further their objectives of assisting in the successful reentry of their clients. This premise aligns with the notion that federal probation officers possess limited control over the predominantly static factors constituting the RPI, as interventions cannot directly alter these factors. Cumulatively, there was a mix of experiences with the RPI, with the majority of feedback expressing a pessimistic perspective.

Overview of Perspectives on the Post-Conviction Risk Assessment (PCRA)

A majority of the conversations with the federal probation officers centered on the PCRA. When discussing its perceived purpose, all of the officers noted its importance in helping identify factors needing to be addressed during the supervision process to help ensure a smooth transition back into the community. This common belief can be tied back to the basic components of RNR, and it showcased, whether they were aware or not, officers' adherence to these influential principles. Another common purpose identified among many of the officers interviewed was that the PCRA determines the level of supervision. Many comments, either directly or indirectly, alluded to this concept. For example, when asked about the purpose of the PCRA, one officer plainly stated, "Gives us a good idea of how often we should be seeing or contacting a person." Indeed, it became evident through conversations that PCRA scores were essential for determining the exact frequency with which officers were required to visit their clients. This obligation becomes important when discussing other concepts related to federal probation officers' perspectives on the dichotomy between actuarial and discretionary judgment, discussed later in the results section.

A further purpose of the PCRA, collectively expressed by the officers, is to serve as an icebreaker and facilitator of further conversation. The officers viewed this strategy as an important part of the supervision process, as it allows them to address two issues at once. The first is to build rapport with their clients, while the second is to showcase to clients what they should be working on during supervision. According to the officers, this allows for more concrete objectives for their clients, which helps steer them away from deviant behaviors. As one of the federal probation officers succinctly put it, “I think it’s an effective tool to help guide conversation.”

A final purpose of the PCRA discussed by all federal probation officers interviewed was its utility in assisting with the selection of individuals for treatment programs, such as Reentry Court. The collected opinions of federal probation officers indicated that risk assessment tools, such as the PCRA, serve as an invaluable source of contextual information for decision-makers. The information gathered helps streamline the process by allowing stakeholders to make well-informed decisions that otherwise would not have been possible. One topic commonly discussed was that the selection, supervision, and treatment of individuals identified as higher risk is a more effective use of resources. This is because individuals who are deemed to be at low risk require comparatively less assistance, due to their relatively fewer issues as compared to those who are at a higher risk level. Within the greater context of limited resources for treatment programs, there was a great appreciation for the ability of risk assessment tools to help make difficult decisions.

Perceptions of Trust. A prominent conviction critical to effective reentry and supervision expressed by all of the federal probation officers was a marked trust in the PCRA. This conviction manifested itself in various discernible forms. One way this was identified was that in most of the interviews, the federal probation officers had little to no negative opinions about the PCRA. In addition, all participants discussed procedures that are contingent upon the utilization of the PCRA. Therefore, although some did not overtly express their trust in the tool, there was a clear belief in at least some parts of its functionality. For instance, the practice of determining what risk factors to address for the supervision process often relies on the PCRA in one capacity or another, particularly for understanding criminal thinking patterns. Interestingly, during one conversation, an officer remarked:

> So if we're going to trust the process and we're going to look at the RNR principles, that's all incorporated into the PCRA. We should be trusting that more and utilizing whatever the results are of that, as long as it continues to be evidence-based.

This assessment not only demonstrates a deep-seated trust in the PCRA, but it also highlights the significance of evidence-based procedures in federal probation officers' decision-making processes. Moreover, it again emphasizes alignment with the fundamental principles of the RNR model. Overall, federal probation officers tended to believe the PCRA is an accurate and useful tool.

Strengths. The federal probation officers identified a variety of strengths of the PCRA. One encompassing strength was its ability to provide a "roadmap" for federal probation officers. The PCRA was widely regarded as an indispensable catalyst for charting supervisory plans by federal probation officers. It reportedly provides them with a consistent framework for approaching offender supervision through its calculation and output, thereby assisting in making informed decisions. In this capacity, it also assists in condensing and simplifying the wide range of factors federal probation officers must consider when planning supervision.

Another unique strength identified by officers is the PCRA's adaptability; specifically, its recognition and emphasis on dynamic factors and flexibility in updating prior scores. As mentioned earlier, federal probation officers tend to perceive dynamic factors as most important when evaluating a case. Therefore, it was readily apparent that many of the officers highly valued the PCRA’s ability to capture several dynamic factors. One factor often discussed was criminal thinking styles, which are measured in the offender assessment section of the PCRA. One officer stated, “The elevated thinking styles and how it pulls out from there is beneficial if I want to have a meaningful strategic conversation with someone to provide some level of opportunity for them to have insight.” This observation not only underscores a marked inclination towards dynamic factors, such as criminal thinking styles, but also holds significant relevance concerning another key strength and perceived general purpose of the PCRA identified by federal probation officers. Specifically, the instrument's efficacy in facilitating meaningful and productive dialogues with clients. This perception was grounded in the recognition of the PCRA's significance in fostering relationships with clients, while simultaneously offering them targeted guidance on areas of focus to mitigate potential risks and prevent future encounters with the criminal justice system.

A final comment on the strength of the PCRA made by one federal probation officer was, “I think it's just to categorize the people that we supervise. It helps group people into different subsets that allow us to evenly disperse our workload.” This perspective slightly varies in its approach to understanding the strength and purpose of the PCRA. Specifically, it is concentrated on the belief that the PCRA’s usefulness lies in its fundamental ability to produce levels of categorization. This process, in turn, designates the amount of resources and supervision time applied to the client with optimal efficiency. This is a marginally different perspective on the PCRA, in that it centers more on the direct and administrative capabilities of the PCRA, rather than thinking of it more as a fluid and multi-purpose system able to provide wide-ranging functions. Nevertheless, this understanding is still critical to acknowledging the demands and limitations of a department’s resources.

Weaknesses. The discussion of weaknesses among federal probation officers varied widely. In addition, as a testament to the trust many officers had, some federal probation officers interviewed did not have any opinions at all as to the potential weaknesses of the PCRA. One weakness explored by two of the officers was offender buy-in when filling out their portion of the PCRA meant to analyze criminal thinking style. One officer reported:

> Anybody can be untruthful when they're filling the PCRA out. They may see something that they think will negatively affect them if they answer a certain way. We certainly try to encourage people to be open and honest in their answers.

The validation process for certain items on the PCRA, such as prior criminal history and supervision noncompliance, is comparatively less complicated. However, establishing the legitimacy of a client's thought process poses significant challenges. Furthermore, one federal probation officer relayed that it is not extremely difficult for clients to ignore adequate forethought when answering the questions posed to them. Only a few measures are coded in reverse to catch whether clients are answering thoughtfully. Another challenge is social desirability bias, which may be particularly relevant given the circumstances of reentry from incarceration. The obvious disadvantage to these scenarios is that federal probation officers must have access to accurate and comprehensive thinking style categorizations. Any inadequacies or omissions in this categorization can render it unusable and, hence, not serve its intended purpose.

Another weakness mentioned by a few of the federal probation officers was the general subjective nature of the scoring system. One officer stated:

> A weakness of the PCRA is officers not having fidelity to the scoring. I think that's kind of a lame answer but it's really a very realistic one because the reality of this tool is that it’s only as good as the person trained to do it and filling it out.

For a few, there was a belief that, despite the actuarial nature of the PCRA, there was still an opportunity for mistakes to occur in the utilization process. Though particular examples were not given, the operation of the PCRA is contingent upon what information is input into its system. Officers could inaccurately input or miss key information, depending on several circumstances. Part of this occurrence can also be derived from how officers are trained and their exposure to risk tool utilization when they are early on in their careers. Furthermore, the issue of subjectivity emphasizes the importance of interrater agreement and how that process is key for the accuracy and consistency of risk assessment scoring systems.

It was mentioned that subjectivity plays a role not only in the final scores derived from the PCRA but also in how these scores influence other elements of supervision, such as the frequency of contact. At times, this subjectivity can result in unfavorable consequences. One of the federal probation officers described a recent situation that served as evidence of this. In the presented scenario, the presiding judge issued an order to raise the score of a client so that they could receive more frequent visits. While such an action may be perceived as favorable in certain cases, in this particular instance, it reportedly hindered the efforts to prevent the individual from engaging in any further wrongdoing. Indeed, the occurrence of over-supervision and the need for certain levels of autonomy were important principles identified by many of the federal probation officers interviewed. Consequently, the configuration of the PCRA and its interconnection with case management occasionally amplifies this issue rather than ameliorating it, especially when confronted with specific circumstances such as the aforementioned scenario.

A further shortcoming of the PCRA noted by one of the federal probation officers interviewed was in regard to the standard procedure for addressing cognition results. Reportedly, this procedure entails scoring and then creating a plan based on the results of the section. This process was perceived as lacking additional deliberation. Specifically, when discussing this concept, the officer commented, “My personal belief is we should have to see their follow-through, not just that they're verbalizing the plan, but they actually have a follow-through that they're doing the plan and that they're addressing it." Indeed, this particular recommendation was concerned with a higher standard for satisfactory completion of case planning tied to risk assessment than is currently in place.

In all, these were the few weaknesses of the PCRA identified by federal probation officers. It is worth noting that a considerable number of the identified issues were not directly attributed to the functional aspects of the PCRA itself but rather emerged as external challenges stemming from factors beyond its immediate control.

Training. Another important process explored in the interviews was the training received for the PCRA. In general, it seemed that the officers were satisfied with the training that was provided to them. The actual process was described as basic risk assessment tool training undergone at the national training academy required for all federal probation agents, followed by annual recertification modules and frequent collaborative events characterized as PCRA "boosters." During these booster events, the officers go over more complex aspects of the PCRA by reading through scoring guides and discussing how one would score mock cases. These events were held in high esteem among the officers, as they provided an opportunity to refresh their skills while also evaluating and building off the scoring analysis of their peers. As one officer put it, "I think the opportunity to have that open dialogue about it really is nailed down by the PCRA coaches. They continue to help at least myself develop with that alert sense." The accounts of this specific officer and other similar descriptions showcase the affinity held for such opportunities.

Despite general satisfaction with the training received for the PCRA, there were still a few suggestions for improvement. One proposition related to a listed purpose and strength of the

PCRA is communication between the federal probation officers and their clients. Specifically, there was a belief that there is an opportunity to improve training on how to discuss PCRA results with clients. The importance of this specific aspect of the PCRA is often overlooked amidst the various other aspects of risk assessment. Therefore, the proposed suggestion warrants careful consideration of how this process can be more effectively taught to federal probation officers. Another suggestion that points to the variability of training exercises and opportunities in separate districts pertains to PCRA audits. One officer described a process in another district where at least three others would evaluate all initial PCRA inputs. This process was reportedly helpful in ensuring the accuracy of the data and results. It was also useful for directing training opportunities for any possible mistakes made. In all, these were a few of the suggestions made for the improvement of PCRA training.

Risk Assessment Challenges and Outlook

Most of the federal probation officers interviewed believed there should be a balance between navigating the actuarial nature of tools while also relying on their subjective experience. One of the first statements made by many of the officers regarding how they approached these divergent operational methods was a reaffirmation of their trust in the PCRA. For example, one officer stated, “I honestly truly believe in the PCRA. I think that it is and should be highly regarded in supervision.” This perceived trust also led a few of the officers to mention how the PCRA was a cornerstone of the supervision process. They relayed the importance back to their initial thoughts of the purpose and strengths of the PCRA.

Some of the officers made it a point to underscore that despite the PCRA's usefulness, it remained imperative for them to give due consideration to their own background and experience. One officer noted:

> But at the same time, if I'm just playing to what this tells me, then I don't think I'm offering them much of an avenue for success. So I utilize my own skills, my tools, my education, and my own understanding of how the world is. On a personal level, kind of understanding being in and understanding the environment from where most of the folks that are on supervision where they come from.

This view coincides with a general understanding that there are still many circumstances or factors to take into consideration that aren't necessarily reflected in risk assessment tools. These factors may lead officers to make or adapt decisions depending on the nature of the case at hand. The aforementioned practice also gives rise to the crucial scenario of score overrides, which holds significant importance in terms of comprehension and analysis.

The federal probation officers interviewed had a more unified view of professional overrides. To reiterate, overrides are occurrences where a score produced by a risk assessment tool is overruled and changed by the officer. The impetus behind overrides described by those being interviewed largely aligns with one of the previously stated purposes of the PCRA, determining the frequency of contact. Most overrides occur when federal probation officers believe they need to visit their clients more than is suggested by the PCRA. One common example cited was with individuals who have committed sex crimes. Despite some ambiguity regarding the procedures followed by officers in handling these cases, it was apparent that the issue of overrides held some salience among them.

Improvements in Risk Assessment Tools

One of the final questions posed entailed assessing federal probation officers' opinions on potential improvements for the PCRA and other risk assessment tools. This particular inquiry elicited one of the most diverse arrays of responses. Almost every officer expressed a unique opinion. A suggestive theme shared by two of the officers was related to the dynamic capabilities of the PCRA. Indeed, one officer took the time to explain the utmost importance of continuity of risk assessment case management with the PCRA and other tools. This officer had difficulty determining any structural changes to the PCRA that could be made to address this critical process but wanted it to be known nonetheless. The other suggestion focused more on a particular function of the PCRA related to these changes. Specifically, it was relayed that federal probation officers can include a "justification" in the files when filling out some information in the PCRA. This merely referred to an area where officers could type out notes as to why something was changed or scored the way it was. The proposition put forth in this instance posited that ensuring uniformity in completing justifications would help federal probation officers gain a more comprehensive understanding of their cases. This consideration is particularly pertinent when considering the demanding nature of their existing workload and the potential risk of inadvertently overlooking significant aspects of any updates.

Two other recommendations comparative in nature were the possibility of additional tools built for more specialized populations of offenders. One officer echoed earlier sentiments about the difficulties of navigating the PCRA and sex offenders while also stating, "I'm sure there are other assessments that are used by sex offender treatment cases, but even for my mental health cases, it'd be nice to have an additional test. Because mental health is an indication for criminal conduct." In this capacity, there appears to be a belief among some federal probation officers that particular categories of offenders necessitate more atypical strategies for effective intervention, something that may not necessarily be reflected in the PCRA. The impact of mental health on supervision was most likely at the forefront of these officers' minds, as it can pose a significant complication to case supervision. Depending on the severity of the condition, officers may encounter difficulties in promoting law-abiding behaviors and identifying cognitive distortions that may be contributing to criminal behavior. Given these complexities, effective supervision of individuals with mental health issues was perceived as requiring a more nuanced and evidence-based approach that accounts for the unique needs and challenges of this population.

Finally, during a few of the discussions, officers hinted at the importance of basing decisions on evidence and the challenges that come with it. It was articulated that research was a critical part of the supervision process. In addition to the fundamental validation of risk assessment tools during their initial implementation, one officer discussing evidence-based practices called back to the overarching theme of continuous evaluation apparent in many of the conversations. It was elucidated how these ongoing endeavors facilitate the attainment of the utmost precision and efficacy in utilizing the available tools. In this case, there appeared to be a profound belief in the ability of data to help drive positive change in the organization. Following up on this line of inquiry, the officer also stated they were unsure if others shared their sentiments about being evidence-based. Accordingly, a potential failure to consistently utilize evidence-based processes was seen as a disservice to the clients.

Another officer relayed that evidence-based practices and research help deal with subjectivity. They commented, “It’s a constant struggle to be objective.” In discussing this conflict, it was seen as imperative to conduct additional research to enhance the overall knowledge base and validate tools that can effectively mitigate subjectivity and potential biases an officer may have when dealing with cases. During other conversations, some were less concerned with the evidence-based elements and mechanics behind risk assessment tools. Rather, they focused more on the basic purposes of risk assessment tools and how they may be used to facilitate effective supervision.

DISCUSSION

The current research sought to address several existing limitations in the field of post-conviction risk assessment. These concerns have revolved around a few points of emphasis. First, there has been a general lack of continued empirical validation for the federal risk assessment tools evaluated. Additionally, most validation studies have not directly addressed the potential capacity for risk assessment instruments to predict potential behaviors beyond rearrest. Furthermore, many of the current studies evaluating federal risk assessment tools have had populations skewed toward a designation of low risk. Finally, there was a general gap related to the contexts and perspectives of federal risk assessment tools from probation officers themselves. Resolving these issues should aid in the ongoing efforts to enhance the practical and perceived efficacy of federal risk assessment instruments.

A mixed-methods approach was taken in order to address the existing limitations. Utilizing data from a previous evaluation of a federal rehabilitation program known as the ACT Reentry Court, associations between a variety of risk factors, federal risk assessment scoring, and behavioral outcomes were identified. Though the approach as a whole was exploratory in nature, several procedures were focused on the fundamental re-verification of the ability of risk tools to predict behavioral outcomes and to be of use to federal probation officers as they help navigate reentry for clients. Given the breadth of useful risk factors in the data, it was important to seek out the various possible statistical relationships displayed between these risk factors and overall risk scores, as well as these factors and behavioral outcomes. Risk factors that may have been statistically associated with the outcomes, but not the federal risk assessment tools, display potential for future examination as prospective additions to the risk assessment tool computation process. The following will highlight the major findings and discuss policy implications, study limitations, and future research directions.

Key Findings

Arguably, the most prominent inquiry addressed in the current study involved the ability of the PCRA and RPI to help forecast future outcomes. The purported goal of the PCRA, according to the AOUSC, is to "improve the effectiveness and efficiency of post-conviction supervision" (Administrative Office of the United States Courts Probation and Pretrial Services Office, 2018, p. 2). One way in which studies evaluating the PCRA have attempted to quantify this is by assessing its ability to predict rearrest (see Johnson et al., 2011; Lowenkamp et al., 2013, 2015; Luallen et al., 2016). The current findings support previous studies, in that PCRA scores were statistically associated with the likelihood of future rearrest. Specifically, those identified by the PCRA as being at greater risk were more likely to be rearrested (see Table 11). In addition, PCRA scores had a statistically significant relationship with probation revocations, drug use, and court outcomes (see Tables 10, 12, and 13). Individuals who scored higher on the PCRA were more likely to have their supervision revoked, fail a drug test, and have an unsuccessful reentry court outcome. This finding speaks to the general ability of the PCRA to predict behavioral outcomes beyond simple rearrest.

Findings from the analysis of the RPI also indicate its general utility as a predictor of rearrest (see Table 14). This discovery follows previously conducted investigations on this tool (Eaglin et al., 1997; Lombard & Hooper, 1998), though the recidivism rates of the current study were more skewed compared to those of Lombard and Hooper (1998). Aside from rearrest, the RPI score was only useful for predicting court outcomes. Individuals with higher RPI scores were more likely to be rearrested and to have unsuccessful reentry court outcomes. Therefore, unlike the PCRA, the RPI does not appear as useful for indicating whether an individual has a higher likelihood of getting their supervision revoked or failing a drug test.

It is also noteworthy that while the bivariate analyses showed significant associations between the risk scores from these tools and certain outcomes, the stepwise logistic regression models developed to further assess outcomes in this study did not contain the PCRA and RPI scores (see Tables 23-26). Although the tools were associated with their respective outcomes, when compiling all factors present in the available data, they were not included among the strongest predictors. These findings concerning multivariate outcome predictors may be attributed to the adherence and facilitation of RNR principles during the Reentry Court program. In other words, the application of RNR through risk assessment seeks to ensure that individuals who demonstrate higher scores receive more comprehensive support and supervision, thus lowering the risk of subsequent negative behavioral outcomes among those who are categorized as medium and higher risk.

Risk Factors and Risk Assessment Tools

Given the composition of different factors and the weighted values of both the RPI and PCRA, most of the findings in this area were in alignment with original expectations. For example, age is a key component of both the PCRA and RPI, and the use of age in these instruments reflects age-graded theories of criminal behavior (e.g., Laub & Sampson, 2001). In the current data, there was a negative and statistically significant relationship between age and the scoring of both federal risk assessment instruments. Those who were older tended to have lower scores on these instruments. Age may even have a stronger predictive effect on behavioral outcomes than the risk tools themselves, as evidenced by the multivariate logistic regression models (see Tables 23-26).

Additionally, factors closely related to past criminal history are included throughout both the RPI and PCRA. That is because previous research indicates past criminal history is often among the strongest predictors of future behavior (Gendreau et al., 1996). Therefore, the various significant correlations identified between components of past criminal history and the risk assessment tools are also aligned with expectations. For example, there was a clear positive association between the total criminal history points from sentencing guidelines and both the PCRA and RPI scores (see Table 15). Other factors reflected the expected pattern as well, including employment and social support (see Tables 16 and 17). Overall, the aforementioned tools demonstrate a commendable ability to synthesize and mirror a substantial portion of the evidence-based information accessible to federal probation officers. Consequently, these tools appear to empower federal probation officers to enhance their service delivery to their clients.

Equally as important as factors that were associated with PCRA and RPI scores are those that had no statistical association. The observed non-correlation between certain risk factors and federal risk assessment tools may be attributed to the exclusion of specific variables that were not deemed relevant to the original predictive capabilities of either instrument. Indeed, this rationale is supported by the current data, as numerous factors that lacked an association with the risk assessment tools also demonstrated no statistically significant relationship with any of the behavioral outcomes. In addition, another example to consider is type of treatment received while in Reentry Court, as type of treatment provided is likely influenced by other aspects of the RNR framework (e.g., responsivity to appropriately recommended treatment). There are a few risk factors, however, that were related to outcomes but not the scores generated by the federal risk assessment tools. One factor in particular that will be discussed in subsequent sections is housing instability.

Risk Factors and Outcomes

The current study included a total of 37 risk variables, categorized into seven major groupings. These included basic demographics, prior criminal sanctions, criminal patterns and violence (CPV), drug-related factors, habitation and court location, mental and physical health, and protective factors. The literature regarding risk factors for future criminal behavior is extremely broad. Nevertheless, a majority of these groups can be classified within the purview of the central eight factors, which are often argued to have the strongest influence on behaviors upon reentry into the community (Bonta & Andrews, 2016). The preeminent classification of variables exhibiting the most robust associations across all groupings was prior criminal sanctions, which included the variables of previous non-compliance, total offense level from guidelines, criminal history points from guidelines, and prison time sentence length. Only prison time sentence length lacked a statistical association with the behavioral outcomes explored.

Apart from this group, there are two additional variables important to address, the first of which is employment. A wealth of literature has demonstrated a negative correlation between employment and subsequent recidivism (e.g., Sampson & Laub, 2003; Uggen et al., 2005). This finding is reflected in the current study through two separate variables measuring employment before and during Reentry Court. One or both of these variables were associated with a decrease in the likelihood of negative outcomes through bivariate correlations, so that employment, overall, had a statistical relationship with all four outcomes (see Tables 19-22). The predictive ability of employment for these outcomes is further apparent through a majority of the multivariate logistic regression models produced, in that those who were employed were much less likely to have their probation revoked, fail a drug test, or have a negative Reentry Court outcome (see Tables 24-26).

Another variable worth mentioning is strong social support. Much like employment, research has consistently found that strong social ties reduce the likelihood of future recidivism (Berg & Huebner, 2011). This observation is also mirrored by the findings of the present study (see Table 19). In addition to rearrest, strong social support was statistically associated with supervision revocation and Reentry Court outcome (see Tables 20 and 22). Those who indicated having strong social support were less likely to have their supervision revoked and were more likely to have a successful outcome for Reentry Court. It is imperative to acknowledge the significance of these associations, as they reveal strong social ties are not only crucial for preventing recidivism, but also for fostering other prosocial behaviors and successful reentry.

Federal Probation Officer Attitudes

Among a number of interesting qualitative findings, the most apparent was the confidence federal probation officers had in the PCRA. This trust is critical, given it is integral to effective oversight, risk mitigation, and predictive capabilities of risk assessment tools (Cohen et al., 2020; Harris et al., 2004; Viglione et al., 2015). The PCRA, and the RPI to some extent, were validated in the previous section, which supports use of these types of tools over personal subjective judgments. Viglione et al. (2015) expound upon this principle by delving deeper into the interrelationship between risk assessment tools and case management processes. Indeed, they recognize a gap still exists in adequately providing probation officers with the resources and supervision environment that support efficient risk management and reentry practices. The current study found that, in terms of the specific federal probation district being evaluated, there were proper resources for integrating risk assessment training with case management practices. Most federal probation officers interviewed felt their training was adequate and that there were proactive ways in which the department continued training and support.

While there was general satisfaction with the PCRA, a few shortcomings were also recognized. A key observation made by one officer, which was also reflected in the quantitative analysis, was the influence of housing instability. When asked which risk factors stood out, a majority of the officers discussed common factors like criminogenic thinking patterns and employment. This is a positive trend, given that these factors have been validated as predictors of reentry success through past research and in the current study (see Sampson & Laub, 2003; Uggen et al., 2005; Walters & Cohen, 2016; Walters & Lowenkamp, 2016). However, the influence of housing instability stood out in the current study because of its statistical association with the majority of the behavioral outcomes in both the bivariate results and the multivariate logistic regression models, while this variable lacked an association with the PCRA and the RPI.

Housing instability was captured by measuring the number of addresses for the Reentry Court participants. Those with a larger number of addresses would be considered to have greater instability (or less stable housing). Previous research conducted in this area has centered on the utilization of incarceration as a predictor of subsequent housing instability, rather than the inverse (e.g., Geller & Curtis, 2011). However, a few studies have found that housing instability increases the likelihood of future arrest (Kirk, 2008; Lutze et al., 2014). In the current research, housing instability was also statistically associated with probation revocation and Reentry Court outcome (Table 18). The findings indicate that a positive relationship exists between the number of reported addresses and the likelihood of experiencing negative outcomes, including rearrest, revocation, and Reentry Court failure.

In addition, there was an understanding that the complexity of offender profiles may warrant tools particularly designed to address the idiosyncrasies of certain clients. During a discussion of overrides and improvements to current risk assessment tools, several federal probation officers touched on topics that have also been part of the evolving conversation among scholars regarding the general utility of risk assessment tools across all types of offenders. For instance, there appeared to be a general recognition that an override from a lower risk level to a higher one tended to occur for those individuals who had committed sex crimes. Research has found that this override often erodes the predictive capabilities of the PCRA (Cohen et al., 2020). Some federal probation officers recognized this and expressed that it may be useful to also utilize specialized risk tools, particularly for this population of offenders. Unfortunately, owing to the limitations imposed on Reentry Court participation, the study lacked data to comprehensively investigate the role of risk assessment and case management for participants who had committed sex crimes.

Beyond sex crimes, the federal probation officers interviewed also alluded to the impact of mental health on both risk assessment and case management. They viewed mental health as a complication in how they might approach a case. Indeed, mental health has long been recognized as a serious issue when it comes to the reentry of justice-involved individuals into the community (e.g., Lurigio et al., 2004). Despite longstanding research, the intersection between risk assessment and mental health is still not well understood. In terms of scored elements, mental health is not computed in the PCRA or RPI. The findings of the current study reinforce this omission, given that none of the variables related to mental health were statistically associated with the criminogenic outcomes. Nevertheless, it may be important to better understand whether mental health issues heavily impact scoring elements of the PCRA and if this affects future outcomes.

Overall, there seemed to be strong buy-in from federal probation officers for current risk assessment practices. Though there were a few suggestions for improvement, all officers interviewed believed the PCRA to be integral to their work. For the most part, this confidence was reflected in the quantitative data, which found strong associations between the PCRA and all outcomes. There was less confidence in the RPI. This dissatisfaction was mirrored both by the quantitative results that found it was associated with fewer behavioral outcomes and through the actions taken by the department to discontinue its use. The results from both types of analysis in this study point toward the emerging importance of continuously evaluating risk assessment instruments and the role federal probation officers play in their enduring usefulness for case supervision and successful reentry.

Policy Implications

A majority of the findings in the current study further validate policies and mandates already enacted by the AOUSC. More broadly, the findings are also mostly in alignment with much of the evidence-based theory and research on reentry and risk assessment. However, the prevalence and impact of risk factors tend to vary across geographical regions. Therefore, there are a few considerations worth noting, particularly for the specific sample being studied. Based on the available data and given the specific risk factors explored, it can be inferred that employment, age, protective factors, and housing instability are among the most prominent predictors of behavioral outcomes within the U.S. District of Connecticut. That is not to suggest that other factors are not associated with behavioral outcomes, but the factors listed had the most consistent and strongest associations in the current study.

Housing instability stood out as a notable factor in the current research. While additional research is necessary to clarify its role in the risk assessment process, it is evident that this factor may warrant increased attention from federal probation officers. That is because, unlike other potential indicators of future behavior, it is not consistently addressed in current risk assessment tools. As such, further consideration of this factor may be necessary for more effective risk assessment and case management. On a more practical level, though a plethora of programs exist that attempt to help alleviate the stressors of housing for those reentering the community, numerous housing barriers continue to hinder a smooth transition. Indeed, a recent report from the Department of Corrections (DOC) in the state of Connecticut found that despite procedures in place, 14% of returnees immediately experienced homelessness (Wilderman et al., 2024). Though this figure encompasses non-federal returnees, the issues surrounding housing instability and reentry as a whole should continue to be addressed.

Furthermore, there should be continued training and departmental emphasis on the dynamic capabilities of the PCRA for case management. Encouraging this approach may help to reduce potential overrides that otherwise might decrease the predictive validity of the PCRA. Potential improvements to training procedures may include additional external reviews of scoring profiles and more in-depth training on how to discuss the scoring system with clients. The prospective benefits of such changes may include increased reliability in scoring across offices, as well as enhanced rapport-building among federal probation officers and their clients. Overall, the principle of better grasping the dynamic systems of the PCRA and its usefulness for case management is an integral message to continue sharing moving forward.

Limitations

There are a few important limitations of the current study to acknowledge. Arguably, the most impactful constraint was the limited sample sizes for both the quantitative (n = 114) and qualitative (n = 6) data. For the quantitative procedures, some variables were left out of the analysis due to severe skewness. A few variables also had to be modified due to low cell counts. However, past studies focused on risk assessment validation also utilized small sample sizes for validation research (e.g., Dyck et al., 2018; Gordon et al., 2015; Mills et al., 2007). In addition, a total of only six federal probation officers were interviewed for the qualitative portion of the study. The exact sample size for qualitative research is mainly a determinant of the study and method addressed (Boddy, 2016). Considering that the number of federal probation officers in the District of Connecticut is much higher, it would have been useful to further verify the results and themes developed by the analysis by interviewing more officers, but this was prevented by limited time and other resources for the current research.

This leads to issues of generalizability, specifically when considering the important emergent theme of the implicit trust and balance of judgment most of the federal probation officers voiced regarding the PCRA's use. In general, it appears there is not a full understanding of overrides, beliefs, and justifications of federal probation officers when using the PCRA across all contexts. For overrides in particular, Cohen et al. (2020) theorized that these overrules may come from a belief on the part of officers that the weights for certain variables are not properly allocated. Whatever the case, it seems clear that overrides reduce the predictive validity of risk assessment tools. A general mistrust of the PCRA may also lead to insufficient case management processes. While the current study's findings suggest that federal probation officers possess a great degree of confidence in the PCRA, it is essential to exercise prudence in interpreting these results. It is plausible that the observed patterns may not accurately represent the attitudes held by federal probation officers in both the studied district and other districts across the United States.

Another consideration is the length of time the current study spans. The median time of supervision for clients in the study was approximately 30 months or 2.5 years. Based on data from the United States Sentencing Commission, the longer an individual spends back in the community, the more likely they are to face a rearrest (Hunt & Dumville, 2016). Therefore, rearrest rates may not be fully accounted for, depending on how long individuals were currently under supervision when the data were collected. While time spent on supervision was controlled for in the multivariate logistic regression models, it was not possible to make such adjustments in the bivariate analyses. Ultimately, the associations between risk factors, the federal risk assessment tools, and the behavioral outcomes may have been partially mediated depending on the supervision time. In a similar realm, the variable of the number of addresses before Reentry Court might also have suffered from temporal-based biases as it was not measured per unit of time. This may be why the number of addresses before Reentry court lacked an association with risk level and behavioral outcomes, among the different housing variables examined.

Future Directions and Conclusion

Given their integral role in the case management process, future research must continue to reassess the validity of risk assessment instruments. Based on the current limitations, it is imperative that subsequent studies explore the utility of these instruments in predicting the behavioral outcomes investigated, and with larger sample sizes. It would also be beneficial to analyze data across multiple districts. This will help support the generalizability of the findings. It will also build stronger data for more comprehensive measurements, considering it will capture a larger part of the target population.

Additionally, it would be useful to assess the ability of risk instruments like the PCRA to predict outcomes beyond what was investigated in the current study. One example would be its capacity to predict the forming or resuming of relationships with antisocial associates after reentry. Moreover, in understanding the tool's predictive capabilities, there is the opportunity to address issues with calibration and computation that may currently be hindering more effective use. There is also potential for realigning objectives with more recent trends in reentry, to attempt to broaden what is defined as a success and how stakeholders like probation officers can better assist clients in their return to the community. There were a few anecdotes presented by officers that shifted the prospective use of the PCRA from an all-encompassing tool meant to provide diverse case management resources to solely an instrument used to ascertain the amount of supervision a client needs. While this approach is not detrimental to the supervision process as a whole, it does not appear as helpful for the facilitation of best practices and thorough case management strategies.

Addressing this perspective will also mitigate overrides in risk assessment. In accordance with previously hypothesized explanations for overrides, the current study found that federal probation officers often rationalized an override as the need for increased supervision for a client (Cohen et al., 2020). This justification may result from a general mistrust of the PCRA's ability to fully encapsulate the weight of a certain risk factor. However, this type of override is often based on a decision to consider a risk factor that is already present in the tool itself, such as substance abuse or noncompliance (Cohen et al., 2020). Further research is necessary to understand the rationale behind overrides and their relation to trust and case management.

The current study also brought to light another important gap that must be further investigated. That is, how special cases impact risk scoring and outcomes for federal risk assessment instruments. A point of emphasis among a few of the federal probation officers was that the PCRA may not be appropriately tuned to address certain special circumstances within their client population. The two most notable cases are sex offenders and the mentally ill. Despite a significant body of research on risk assessment methodologies designed to address individuals who committed sex crimes, the empirical evaluation of the mental health component of risk assessment instruments remains scarce (e.g., Barbaree et al., 2001; Beech et al., 2003; Hanson & Thornton, 2000).

To date, few studies have investigated the effectiveness of these tools in assessing the mental health aspects of individuals involved in criminal activity. It is therefore imperative to persist in the exploration and development of effective strategies aimed at evaluating the mental health dimensions of risk assessment instruments. Although there was little relationship established between variables related to mental health and outcomes or instruments in the current study, it remains important to continue investigating how these circumstances may impact scoring and outcomes. There is also the possibility that the impact of mental illness is dependent on the specific risk tool being examined, and therefore, may not impact PCRA or RPI scoring outcomes. For instance, Skeem et al. (2014) found that there was no difference in the predictive ability of risk assessment instruments for those with mental illnesses for the LS/CMI and another tool known as the HCR-20 (Webster et al., 1997). Meanwhile, Wardrop (2020) investigated this phenomenon with a separate post-conviction risk assessment tool called the Dynamic Risk Assessment for Offender Re-Entry (DRAOR; Serin, 2007) and found that it was less accurate for those with a diagnosed mental illness.

Overall, these suggestions provide an adequate basis for further exploration of the relationship between federal risk assessment tools and behavioral outcomes. In doing so, researchers might better identify practices geared toward the improvement of risk assessment instruments for those returning from federal incarceration. The realm of risk assessment can often be nuanced and confusing. As such, continued validation and research can help to clarify the utility of these instruments. Additionally, understanding the context surrounding the use of federal risk assessment instruments by probation officers may reveal important relationships that have yet to be fully exposed. Ultimately, risk assessment research will be crucial for helping build a knowledge base that can, in turn, help reduce the negative outcomes of reentry into the community.

Appendix A

Full Tables from Quantitative Analysis

Table A1

Chi-Square Crosstabs – General Risk Factors & PCRA Full

Factors		Low-Low/Mod		Mod-High		Total		X^2	φ
		n	%	n	%	n	%		
Race/Ethnicity	Caucasian	3	30.0%	7	70.0%	10	100.0%	2.827	.157
	White Hispanic	8	50.0%	8	50.0%	16	100.0%		
	African American	29	33.7%	57	66.3%	86	100.0%		
	Black Hispanic	0	0.0%	2	100.0%	2	100.0%		
Single	No	11	39.3%	17	60.7%	28	100.0%	.287	.050
	Yes	29	33.7%	57	66.3%	86	100.0%		
Obtained GED	No	13	27.1%	35	72.9%	48	100.0%	2.332	-.143
	Yes	27	40.9%	39	59.1%	66	100.0%		
Employment at Start	No	27	34.2%	52	65.8%	79	100.0%	.094	-.029
	Yes	13	37.1%	22	62.9%	35	100.0%		
Employment During	No	3	17.6%	14	82.4%	17	100.0%	.2668	-.153
	Yes	37	38.1%	60	61.9%	97	100.0%		
Pre Reentry Court Non-Compliance	No	33	40.2%	49	59.8%	82	100.0%	3.410	.173
	Yes	7	21.9%	25	78.1%	32	100.0%		
Criminal Activity on Supervision	No	30	44.1%	38	55.9%	68	100.0%	**6.033***	.230
	Yes	10	21.7%	36	78.3%	46	100.0%		
Pattern of Similar Criminal Activity	No	26	44.8%	32	55.2%	58	100.0%	**4.918***	.208
	Yes	14	25.0%	42	75.0%	56	100.0%		
Criminal Associations	No	28	35.0%	52	65.0%	80	100.0%	.001	-.003
	Yes	12	35.3%	22	64.7%	34	100.0%		
Prior Weapon Charges	No	37	44.0%	47	56.0%	84	100.0%	**11.251****	.314
	Yes	3	10.0%	27	90.0%	30	100.0%		
Other Violence	No	30	36.6%	52	63.4%	82	100.0%	.288	.050
	Yes	10	31.3%	22	68.8%	32	100.0%		
Institutional Adjustment problems	No	36	39.1%	56	60.9%	92	100.0%	3.421	.173
	Yes	4	18.2%	18	81.8%	22	100.0%		
Domestic Violence	No	35	36.8%	60	63.2%	95	100.0%	.770	.082
	Yes	5	26.3%	14	73.7%	19	100.0%		

**$P \le .01$; *$P \le .05$

Table A1 Continued

Factors		Low-Low/Mod n	Low-Low/Mod %	Mod-High n	Mod-High %	Total n	Total %	X^2	φ
Gang Involvement	No	37	37.0%	63	63.0%	100	100.0%	1.307	.107
	Yes	3	21.4%	11	78.6%	14	100.0%		
Pending Charges	No	38	34.9%	71	65.1%	109	100.0%	.055	-.022
	Yes	2	40.0%	3	60.0%	5	100.0%		
Convicted of a Drug Charge	No	11	32.4%	23	67.6%	34	100.0%	.159	-.037
	Yes	29	36.3%	51	63.8%	80	100.0%		
Prior Hard Drug Use	No	23	46.9%	26	53.1%	49	100.0%	**5.299***	.216
	Yes	17	26.2%	48	73.8%	65	100.0%		
Court Location	New Haven	12	44.4%	15	55.6%	27	100.0%	3.722	.181
	Bridgeport	7	21.9%	25	78.1%	32	100.0%		
	Hartford	21	38.2%	34	61.8%	55	100.0%		
Medical Issue or Disorder	No	33	38.4%	53	61.6%	86	100.0%	1.658	.121
	Yes	7	25.0%	21	75.0%	28	100.0%		
Evidence of a Mental Disorder	No	8	20.0%	32	80.0%	40	100.0%	**6.159***	-.232
	Yes	32	43.2%	42	56.8%	74	100.0%		
Treatment in Reentry Court	None	8	42.1%	11	57.9%	19	100.0%	2.249	.140
	Mental	12	30.8%	27	69.2%	39	100.0%		
	Rehab	10	45.5%	12	54.5%	22	100.0%		
	Both	10	29.4%	24	70.6%	34	100.0%		
Motivated to Change	No	8	21.1%	30	78.9%	38	100.0%	**4.930***	-.208
	Yes	32	42.1%	44	57.9%	76	100.0%		
Strong Social Support	No	9	18.8%	39	81.3%	48	100.0%	**9.716****	-.292
	Yes	31	47.0%	35	53.0%	66	100.0%		
Good Work History	No	33	32.4%	69	67.6%	102	100.0%	3.182	-.167
	Yes	7	58.3%	5	41.7%	12	100.0%		
Reliable Source of Adequate Income	No	29	30.5%	66	69.5%	95	100.0%	**5.207***	-.214
	Yes	11	57.9%	8	42.1%	19	100.0%		
Special Work Skills	No	37	37.0%	63	63.0%	10	100.0%	1.307	.107
	Yes	3	21.4%	11	78.6%	14			

$^{**}p \leq .01$; $^{*}p \leq .05$

Table A2

T-Test for Risk Factors and RPI Full

Factors		N	M	SD	*t*(85)	Cohen's d
Single	No	17	4.41	2.002	-1.505	.407
	Yes	70	5.17	1.833		
Obtained GED	No	39	5.41	1.802	1.750	.379
	Yes	47	4.70	1.921		
Employment at Start	No	63	5.03	1.900	.070	.017
	Yes	24	5.00	1.865		
Employment During	No	15	5.67	1.113	**1.467***	.416
	Yes	72	4.89	1.983		
Pre Reentry Court Non-Compliance	No	64	4.84	1.937	-1.494	.363
	Yes	23	5.52	1.648		
Criminal Activity on Supervision	No	59	4.93	2.042	-.652	.150
	Yes	28	5.21	1.500		
Pattern of Similar Criminal Activity	No	49	4.92	2.149	-.587	.127
	Yes	38	5.16	1.480		
Criminal Associations	No	61	5.03	2.016	.074	.017
	Yes	26	5.00	1.549		
Prior Weapon Charges	No	67	4.90	1.947	-1.160	.296
	Yes	20	5.45	1.605		
Other Violence	No	68	5.04	1.927	.197	.051
	Yes	19	4.95	1.747		
Institutional Adjustment problems	No	72	4.96	1.960	-.701	.199
	Yes	15	5.33	1.447		
Domestic Violence	No	73	4.93	1.960	-1.037	.303
	Yes	14	5.50	1.345		
Gang Involvement	No	76	4.96	1.907	-.813	.262
	Yes	11	5.45	1.695		
Pending Charges	No	83	5.01	1.916	-.246	.126
	Yes	4	5.25	.957		
Convicted of a Drug Charge	No	27	5.26	2.068	.785	.182
	Yes	60	4.92	1.797		

$^{**}p \leq .01$; $^{*}p \leq .05$

Table A2 Continued

		n	M	SD	$t(85)$	Cohen's d
Prior Hard Drug Use	No	41	4.68	2.161	-1.607	.345
	Yes	46	5.33	1.550		
Medical Issue or Disorder	No	66	5.09	1.862	.595	.149
	Yes	21	4.81	1.965		
Evidence of a Mental Disorder	No	26	5.50	1.581	1.558	.365
	Yes	61	4.82	1.971		
Motivated to Change	No	29	5.83	1.891	**2.946****	.670
	Yes	58	4.62	1.755		
Strong Social Support	No	37	5.84	1.803	**3.730****	.809
	Yes	50	4.42	1.715		
Good Work History	No	75	5.04	1.941	.210	.065
	Yes	12	4.92	1.505		
Reliable Source of Adequate Income	No	72	5.15	1.896	1.419	.403
	Yes	15	4.40	1.724		
Special Work Skills	No	74	4.95	1.937	-.911	.274
	Yes	13	5.46	1.506		

$^{**}p \leq .01$; $^{*}p \leq .05$

Table A3

ANOVA Variables Risk Factors and RPI Score

		M	SD	F	η^2
Race	Caucasian	4.57	1.134	1.643 (3, 83)	.056
	White Hispanic	3.75	2.315		
	African American	5.20	1.870		
	Black Hispanic	5.5	.707		
Court location	Bridgeport	4.50	1.395	1.310 (2, 84)	.030
	Hartford	5.45	2.350		
	New Haven	5.06	1.823		
Treatment type	None	4.33	1.676	1.642 (3, 83)	.054
	Substance Abuse Treatment	5.24	1.707		
	Mental Health Treatment	4.53	2.326		
	Both	5.48	1.855		

$^{**}p \leq .01$; $^{*}p \leq .05$

Table A4

Chi-Squared Crosstabs – Factors and Rearrest Full

Factors		No Rearrest		Rearrest		Total		X^2	φ
		n	%	n	%	n	%		
Race/Ethnicity	Caucasian	7	70.0%	3	30.0%	10	100.0%	4.875	.221
	White Hispanic	14	87.5%	2	12.5%	16	100.0%		
	African American	56	65.1%	30	34.9%	86	100.0%		
	Black Hispanic	1	50.0%	1	50.0%	2	100.0%		
Single	No	23	82.1%	5	17.9%	28	100.0%	3.234	.168
	Yes	55	64.0%	31	36.0%	86	100.0%		
Obtained GED	No	30	62.5%	18	37.5%	48	100.0%	1.345	-.109
	Yes	48	72.7%	18	27.3%	66	100.0%		
Employment at Start	No	55	69.6%	24	30.4%	79	100.0%	.171	.039
	Yes	23	65.7%	12	34.3%	35	100.0%		
Employment During	No	8	47.1%	9	52.9%	17	100.0%	**4.220***	-.192
	Yes	70	72.2%	27	27.8%	97	100.0%		
Pre Reentry Court Non-Compliance	No	60	73.2%	22	26.8%	82	100.0%	3.050	.164
	Yes	18	56.3%	14	43.8%	32	100.0%		
Criminal Activity on Supervision	No	47	69.1%	21	30.9%	68	100.0%	.038	.018
	Yes	31	67.4%	15	32.6%	46	100.0%		
Pattern of Similar Criminal Activity	No	37	63.8%	21	36.2%	58	100.0%	1.170	-.101
	Yes	41	73.2%	15	26.8%	56	100.0%		
Criminal Associations	No	55	68.8%	25	31.3%	80	100.0%	.013	.011
	Yes	23	67.6%	11	32.4%	34	100.0%		
Prior Weapon Charges	No	58	69.0%	26	31.0%	84	100.0%	.058	.023
	Yes	20	66.7%	10	33.3%	30	100.0%		
Other Violence	No	55	67.1%	27	32.9%	82	100.0%	.246	-.046
	Yes	23	71.9%	9	28.1%	32	100.0%		
Institutional Adjustment problems	No	65	70.7%	27	29.3%	92	100.0%	1.098	.098
	Yes	13	59.1%	9	40.9%	22	100.0%		
Domestic Violence	No	66	69.5%	29	30.5%	95	100.0%	.292	.051
	Yes	12	63.2%	7	36.8%	19	100.0%		
Gang Involvement	No	71	71.0%	29	29.0%	100	100.0%	2.507	.148
	Yes	7	50.0%	7	50.0%	14	100.0%		
Pending Charges	No	73	67.0%	36	33.0%	109	100.0%	2.414	-.146
	Yes	5	100.0%	0	0.0%	5	100.0%		

$**p \leq .01$; $*p \leq .05$

Table A4 Continued

Factors		No Rearrest		Rearrest		Total		X^2	φ
		n	%	n	%	n	%		
Convicted of a Drug Charge	No	22	64.7%	12	35.3%	34	100.0%	.310	-.052
	Yes	56	70.0%	24	30.0%	80	100.0%		
Prior Hard Drug Use	No	34	69.4%	15	30.6%	49	100.0%	.037	.018
	Yes	44	67.7%	21	32.3%	65	100.0%		
Court Location	New Haven	23	85.2%	4	14.8%	27	100.0%	**6.988***	.248
	Bridgeport	17	53.1%	15	46.9%	32	100.0%		
	Hartford	38	69.1%	17	30.9%	55	100.0%		
Medical Issue or Disorder	No	57	66.3%	29	33.7%	86	100.0%	.744	-.081
	Yes	21	75.0%	7	25.0%	28	100.0%		
Evidence of a Mental Disorder	No	23	57.5%	17	42.5%	40	100.0%	3.402	-.173
	Yes	55	74.3%	19	25.7%	74	100.0%		
Treatment in Reentry Court	None	14	73.7%	5	26.3%	19	100.0%	4.749	.191
	Mental	22	56.4%	17	43.6%	39	100.0%		
	Rehab	18	81.8%	4	18.2%	22	100.0%		
	Both	24	70.6%	10	29.4%	34	100.0%		
Motivated to Change	No	23	60.5%	15	39.5%	38	100.0%	1.644	-.120
	Yes	55	72.4%	21	27.6%	76	100.0%		
Strong Social Support	No	25	52.1%	23	47.9%	48	100.0%	**10.242****	-.300
	Yes	53	80.3%	13	19.7%	66	100.0%		
Good Work History	No	70	68.6%	32	31.4%	102	100.0%	.019	.013
	Yes	8	66.7%	4	33.3%	12	100.0%		
Reliable Source of Adequate Income	No	64	67.4%	31	32.6%	95	100.0%	.292	-.051
	Yes	14	73.7%	5	26.3%	19	100.0%		
Special Work Skills	No	70	70.0%	30	30.0%	100	100.0%	.940	.091
	Yes	8	57.1%	6	42.9%	14	100.0%		

**$p \leq .01$; *$p \leq .05$

Table A5

Chi-Squared Crosstabs – Factors and Revocation Full

Factors		No Revocation		Revocation		Total		X^2	φ
		n	%	n	%	n	%		
Race/Ethnicity	Caucasian	8	80.0%	2	20.0%	10	100.0%	5.317	.216
	White Hispanic	16	100.0%	0	0.0%	16	100.0%		
	African American	68	79.1%	18	20.9%	86	100.0%		
	Black Hispanic	1	50.0%	1	50.0%	2	100.0%		
Single	No	25	89.3%	3	10.7%	28	100.0%	1.467	.113
	Yes	68	79.1%	18	20.9%	86	100.0%		
Obtained GED	No	36	75.0%	12	25.0%	48	100.0%	2.388	-.145
	Yes	57	86.4%	9	13.6%	66	100.0%		
Employment at Start	No	62	78.5%	17	21.5%	79	100.0%	1.643	-.120
	Yes	31	88.6%	4	11.4%	35	100.0%		
Employment During	No	7	41.2%	10	58.8%	17	100.0%	**21.702****	-.436
	Yes	86	88.7%	11	11.3%	97	100.0%		
Pre Reentry Court Non-Compliance	No	72	87.8%	10	12.2%	82	100.0%	**7.535***	.257
	Yes	21	65.6%	11	34.4%	32	100.0%		
Criminal Activity on Supervision	No	56	82.4%	12	17.6%	68	100.0%	.067	.024
	Yes	37	80.4%	9	19.6%	46	100.0%		
Pattern of Similar Criminal Activity	No	44	75.9%	14	24.1%	58	100.0%	2.568	-.150
	Yes	49	87.5%	7	12.5%	56	100.0%		
Criminal Associations	No	64	80.0%	16	20.0%	80	100.0%	.445	-.062
	Yes	29	85.3%	5	14.7%	34	100.0%		
Prior Weapon Charges	No	70	83.3%	14	16.7%	84	100.0%	.654	.076
	Yes	23	76.7%	7	23.3%	30	100.0%		
Other Violence	No	67	81.7%	15	18.3%	82	100.0%	.003	.005
	Yes	26	81.3%	6	18.8%	32	100.0%		
Institutional Adjustment problems	No	78	84.8%	14	15.2%	92	100.0%	3.256	.169
	Yes	15	68.2%	7	31.8%	22	100.0%		
Domestic Violence	No	78	82.1%	17	17.9%	95	100.0%	.105	.030
	Yes	15	78.9%	4	21.1%	19	100.0%		
Gang Involvement	No	85	85.0%	15	15.0%	100	100.0%	**6.342***	.236
	Yes	8	57.1%	6	42.9%	14	100.0%		
Pending Charges	No	88	80.7%	21	19.3%	109	100.0%	1.181	-.102
	Yes	5	100.0%	0	0.0%	5	100.0%		

**$p \leq .01$; *$p \leq .05$

Table A5 Continued

Factors		No Revocation		Revocation		Total		X^2	φ
		n	%	n	%	n	%		
Convicted of a Drug Charge	No	26	76.5%	8	23.5%	34	100.0%	.841	-.086
	Yes	67	83.8%	13	16.3%	80	100.0%		
Prior Hard Drug Use	No	39	79.6%	10	20.4%	49	100.0%	.226	-.045
	Yes	54	83.1%	11	16.9%	65	100.0%		
Court Location	New Haven	25	92.6%	2	7.4%	27	100.0%	3.192	.167
	Bridgeport	24	75.0%	8	25.0%	32	100.0%		
	Hartford	44	80.0%	11	20.0%	55	100.0%		
Medical Issue or Disorder	No	70	81.4%	16	18.6%	86	100.0%	.008	-.008
	Yes	23	82.1%	5	17.9%	28	100.0%		
Evidence of a Mental Disorder	No	30	75.0%	10	25.0%	40	100.0%	1.775	-.125
	Yes	63	85.1%	11	14.9%	74	100.0%		
Treatment in Reentry Court	None	15	78.9%	4	21.1%	19	100.0%	4.849	.206
	Mental	28	71.8%	11	28.2%	39	100.0%		
	Rehab	20	90.9%	2	9.1%	22	100.0%		
	Both	30	88.2%	4	11.8%	34	100.0%		
Motivated to Change	No	30	78.9%	8	21.1%	38	100.0%	.263	-.048
	Yes	63	82.9%	13	17.1%	76	100.0%		
Strong Social Support	No	35	72.9%	13	27.1%	48	100.0%	**4.140***	-.191
	Yes	58	87.9%	8	12.1%	66	100.0%		
Good Work History	No	82	80.4%	20	19.6%	102	100.0%	.908	-.089
	Yes	11	91.7%	1	8.3%	12	100.0%		
Reliable Source of Adequate Income	No	76	80.0%	19	20.0%	95	100.0%	.946	-.091
	Yes	17	89.5%	2	10.5%	19	100.0%		
Special Work Skills	No	82	82.0%	18	18.0%	100	100.0%	.096	.029
	Yes	11	78.6%	3	21.4%	14	100.0%		

**p ≤ .01; *p ≤ .05

Table A6

Chi-Squared Crosstabs – Factors and Drug Use Full

Factors		Negative		Positive		Total		X^2	φ
		n	%	n	%	n	%		
Race/Ethnicity	Caucasian	3	30.0%	7	70.0%	10	100.0%	5.580	.221
	White Hispanic	11	68.8%	5	31.3%	16	100.0%		
	African American	52	60.5%	34	39.5%	86	100.0%		
	Black Hispanic	2	100.0%	0	0.0%	2	100.0%		
Single	No	19	67.9%	9	32.1%	28	100.0%	1.039	.095
	Yes	49	57.0%	37	43.0%	86	100.0%		
Obtained GED	No	26	54.2%	22	45.8%	48	100.0%	1.035	.095
	Yes	42	63.6%	24	36.4%	66	100.0%		
Employment at Start	No	42	53.2%	37	46.8%	79	100.0%	**4.495***	.199
	Yes	26	74.3%	9	25.7%	35	100.0%		
Employment During	No	8	47.1%	9	52.9%	17	100.0%	1.316	.107
	Yes	60	61.9%	37	38.1%	97	100.0%		
Pre Reentry Court Non-Compliance	No	54	65.9%	28	34.1%	82	100.0%	**4.672***	.202
	Yes	14	43.8%	18	56.3%	32	100.0%		
Criminal Activity on Supervision	No	40	58.8%	28	41.2%	68	100.0%	.048	.020
	Yes	28	60.9%	18	39.1%	46	100.0%		
Pattern of Similar Criminal Activity	No	33	56.9%	25	43.1%	58	100.0%	.372	.057
	Yes	35	62.5%	21	37.5%	56	100.0%		
Criminal Associations	No	47	58.8%	33	41.3%	80	100.0%	.090	.028
	Yes	21	61.8%	13	38.2%	34	100.0%		
Prior Weapon Charges	No	52	61.9%	32	38.1%	84	100.0%	.675	.077
	Yes	16	53.3%	14	46.7%	30	100.0%		
Other Violence	No	49	59.8%	33	40.2%	82	100.0%	.001	.003
	Yes	19	59.4%	13	40.6%	32	100.0%		
Institutional Adjustment problems	No	54	58.7%	38	41.3%	92	100.0%	.180	.040
	Yes	14	63.6%	8	36.4%	22	100.0%		
Domestic Violence	No	59	62.1%	36	37.9%	95	100.0%	1.429	.112
	Yes	9	47.4%	10	52.6%	19	100.0%		
Gang Involvement	No	60	60.0%	40	40.0%	100	100.0%	.042	.019
	Yes	8	57.1%	6	42.9%	14	100.0%		
Pending Charges	No	64	58.7%	45	41.3%	109	100.0%	.900	.089
	Yes	4	80.0%	1	20.0%	5	100.0%		

**$p \leq .01$; *$p \leq .05$

Table A6 Continued

Factors		Negative		Positive		Total		X^2	φ
		n	%	n	%	n	%		
Convicted of a Drug Charge	No	22	64.7%	12	35.3%	34	100.0%	.515	.067
	Yes	46	57.5%	34	42.5%	80	100.0%		
Prior Hard Drug Use	No	28	57.1%	21	42.9%	49	100.0%	.224	.044
	Yes	40	61.5%	25	38.5%	65	100.0%		
Court Location	New Haven	18	66.7%	9	33.3%	27	100.0%	1.898	.129
	Bridgeport	16	50.0%	16	50.0%	32	100.0%		
	Hartford	34	61.8%	21	38.2%	55	100.0%		
Medical Issue or Disorder	No	54	62.8%	32	37.2%	86	100.0%	1.436	.112
	Yes	14	50.0%	14	50.0%	28	100.0%		
Evidence of a Mental Disorder	No	24	60.0%	16	40.0%	40	100.0%	.003	.005
	Yes	44	59.5%	30	40.5%	74	100.0%		
Treatment in Reentry Court	None	11	57.9%	8	42.1%	19	100.0%	6.763	.244
	Mental	23	59.0%	16	41.0%	39	100.0%		
	Rehab	18	81.8%	4	18.2%	22	100.0%		
	Both	16	47.1%	18	52.9%	34	100.0%		
Motivated to Change	No	20	52.6%	18	47.4%	38	100.0%	1.166	.101
	Yes	48	63.2%	28	36.8%	76	100.0%		
Strong Social Support	No	26	54.2%	22	45.8%	48	100.0%	1.035	.095
	Yes	42	63.6%	24	36.4%	66	100.0%		
Good Work History	No	59	57.8%	43	42.2%	102	100.0%	1.313	.107
	Yes	9	75.0%	3	25.0%	12	100.0%		
Reliable Source of Adequate Income	No	57	60.0%	38	40.0%	95	100.0%	.029	.016
	Yes	11	57.9%	8	42.1%	19	100.0%		
Special Work Skills	No	58	58.0%	42	42.0%	100	100.0%	.920	.337
	Yes	10	71.4%	4	28.6%	14	100.0%		

**$p \leq .01$; *$p \leq .05$

Table A7

Chi-Squared Crosstabs – Factors and Court Outcome Full

Factors		Failure		Success		Total		X^2	φ
		n	%	n	%	n	%		
Race/Ethnicity	Caucasian	4	50.0%	4	50.0%	8	100.0%	4.875	.221
	White Hispanic	2	15.4%	11	84.6%	13	100.0%		
	African American	28	35.9%	50	64.1%	78	100.0%		
	Black Hispanic	1	100.0%	0	0.0%	1	100.0%		
Single	No	3	13.0%	20	87.0%	23	100.0%	**6.330***	-.252
	Yes	32	41.6%	45	58.4%	77	100.0%		
Obtained GED	No	21	47.7%	23	52.3%	44	100.0%	**5.594***	.237
	Yes	14	25.0%	42	75.0%	56	100.0%		
Employment at Start	No	27	38.6%	43	61.4%	70	100.0%	1.308	.114
	Yes	8	26.7%	22	73.3%	30	100.0%		
Employment During	No	13	92.9%	1	7.1%	14	100.0%	**23.953****	.489
	Yes	22	25.6%	64	74.4%	86	100.0%		
Pre Reentry Court Non-Compliance	No	21	28.0%	54	72.0%	75	100.0%	**6.462***	-.254
	Yes	14	56.0%	11	44.0%	25	100.0%		
Criminal Activity on Supervision	No	22	36.1%	39	63.9%	61	100.0%	.078	.028
	Yes	13	33.3%	26	66.7%	39	100.0%		
Pattern of Similar Criminal Activity	No	22	40.7%	32	59.3%	54	100.0%	1.701	.130
	Yes	13	28.3%	33	71.7%	46	100.0%		
Criminal Associations	No	24	34.3%	46	65.7%	70	100.0%	.052	-.023
	Yes	11	36.7%	19	63.3%	30	100.0%		
Prior Weapon Charges	No	25	33.3%	50	66.7%	75	100.0%	.366	-.061
	Yes	10	40.0%	15	60.0%	25	100.0%		
Other Violence	No	26	36.1%	46	63.9%	72	100.0%	.140	.037
	Yes	9	32.1%	19	67.9%	28	100.0%		
Institutional Adjustment problems	No	27	33.3%	54	66.7%	81	100.0%	.521	-.072
	Yes	8	42.1%	11	57.9%	19	100.0%		
Domestic Violence	No	27	32.1%	57	67.9%	84	100.0%	1.884	-.137
	Yes	8	50.0%	8	50.0%	16	100.0%		
Gang Involvement	No	27	31.4%	59	68.6%	86	100.0%	3.508	-.187
	Yes	8	57.1%	6	42.9%	14	100.0%		
Pending Charges	No	35	36.8%	60	63.2%	95	100.0%	2.834	.168
	Yes	0	0.0%	5	100.0%	5	100.0%		

**$p \leq .01$; *$p \leq .05$

Table A7 Continued

Factors		Failure		Success		Total		X^2	φ
		n	%	n	%	n	%		
Convicted of a Drug Charge	No	12	42.9%	16	57.1%	28	100.0%	1.055	.103
	Yes	23	31.9%	49	68.1%	72	100.0%		
Prior Hard Drug Use	No	18	40.0%	27	60.0%	45	100.0%	.899	.095
	Yes	17	30.9%	38	69.1%	55	100.0%		
Court Location	New Haven	6	28.6%	15	71.4%	21	100.0%	4.617	.215
	Bridgeport	14	51.9%	13	48.1%	27	100.0%		
	Hartford	15	28.8%	37	71.2%	52	100.0%		
Medical Issue or Disorder	No	27	35.1%	50	64.9%	77	100.0%	.001	.002
	Yes	8	34.8%	15	65.2%	23	100.0%		
Evidence of a Mental Disorder	No	15	41.7%	21	58.3%	36	100.0%	1.099	.105
	Yes	20	31.3%	44	68.8%	64	100.0%		
Treatment in Reentry Court	None	5	31.3%	11	68.8%	16	100.0%	4.541	.213
	Mental	17	47.2%	19	52.8%	36	100.0%		
	Rehab	4	20.0%	16	80.0%	20	100.0%		
	Both	9	32.1%	19	67.9%	28	100.0%		
Motivated to Change	No	14	46.7%	16	53.3%	30	100.0%	2.564	.160
	Yes	21	30.0%	49	70.0%	70	100.0%		
Strong Social Support	No	21	52.5%	19	47.5%	40	100.0%	**8.974****	.300
	Yes	14	23.3%	46	76.7%	60	100.0%		
Good Work History	No	33	36.3%	58	63.7%	91	100.0%	.710	.084
	Yes	2	22.2%	7	77.8%	9	100.0%		
Reliable Source of Adequate Income	No	31	36.9%	53	63.1%	84	100.0%	.837	.092
	Yes	4	25.0%	12	75.0%	16	100.0%		
Special Work Skills	No	32	36.4%	56	63.6%	88	100.0%	.599	.077
	Yes	3	25.0%	9	75.0%	12	100.0%		

**$p \leq .01$; *$p \leq .05$

Appendix B

Interview Questions

Risk Assessment Instruments:

1. What does risk assessment mean to you?
    a. Why is it used?
2. Describe the PCRA and how it is utilized in the process of your daily operations.
3. What are the strengths of the PCRA?
4. What are the weaknesses of the PCRA?
5. Does the PCRA allow for a mix of actuarial and professional judgement?
    a. What is preferred? Clinical judgement, complete actuarial assessment, or a combination?
    b. Should actuarial tools reinforce clinical judgment or supplant it?
    c. Are there opportunity and circumstances for an assessment override?

Risk Factors:

6. What is your level of knowledge and understanding of risk factors?
7. What risk factors stand out the most?
8. Are there any risk factors you believe are missing from the tools you use?

Processes/Outcomes:

9. Is there adequate or better risk assessment tool training?
    a. Should it be an ongoing process? Annual recertification?
10. Is there satisfactory evaluation of risk assessment tool effectiveness?
    a. Are there sufficient quality control mechanisms?
    b. Are tools consistently updated?
11. What is the importance of risk assessment tools, specifically in relation to reentry programs?
12. How helpful are risk assessment tools in designating proper resources and in the reentry decision-making process?
13. What should the focus of these instruments be in relation to the prediction of outcomes?
    a. What are your thoughts on the way instruments and reentry success are perceived and potentially related?
14. Is there anything that can be done to improve RA tools? If so, what?

References

Administrative Office of the United States Courts Probation and Pretrial Services Office. (2018). *An Overview of the Federal Post Conviction Risk Assessment*. https://www.uscourts.gov/sites/default/files/overview_of_the_post_conviction_risk_assessment_0.pdf

Andrews, D. A. (1982). A personal, interpersonal and community-reinforcement perspective on deviant behaviour (PIC-R). *Ontario Ministry of Correctional Services, Planning and Support Services Division, Planning and Research Branch.*, 1–69.

Andrews, D. A., & Bonta, J. (2000). *The level of service inventory-revised*. Multi-Health Systems.

Andrews, D. A., Bonta, J., & Wormith, J. S. (2006). The recent past and near future of risk and/or need assessment. *Crime & Delinquency*, *52*(1), 7–27. https://doi.org/10.1177/0011128705281756

Andrews, D., Bonta, J., & Wormith, J. S. (2004). *The Level of Service/Case Management Inventory*. https://doi.org/10.1037/t05029-000

Ashford, J. B., Wong, K. W., & Sternbach, K. O. (2008). Generic correctional programming for mentally ill offenders: A pilot study. *Criminal Justice and Behavior*, *35*(4), 457–473. https://doi.org/10.1177/0093854807313356

Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. *European Journal of Operational Research*, *253*(1), 1–13. https://doi.org/10.1016/j.ejor.2015.12.023

Barbaree, H. E., Seto, M. C., Langton, C. M., & Peacock, E. J. (2001). Evaluating the predictive accuracy of six risk assessment instruments for adult sex offenders. *Criminal justice and behavior*, *28*(4), 490-521. https://doi.org/10.1177/009385480102800406

Beech, A. R., Fisher, D. D., & Thornton, D. (2003). Risk assessment of sex offenders. *Professional Psychology: Research and Practice*, *34*(4), 339. https://doi.org/10.1037/0735-7028.34.4.339

Bennett, T., Holloway, K., & Farrington, D. (2008). The statistical association between drug misuse and crime: A meta-analysis. *Aggression and Violent Behavior*, *13*(2), 107–118. https://doi.org/10.1016/j.avb.2008.02.001

Berg, M. T., & Huebner, B. M. (2011). Reentry and the ties that bind: An examination of social ties, employment, and recidivism. *Justice quarterly*, 28(2), 382-410. https://doi.org/10.1080/07418825.2010.498383

Bjerk, D. (2007). Measuring the relationship between youth criminal participation and household economic resources. *Journal of Quantitative Criminology*, *23*(1), 23–39. https://doi.org/10.1007/s10940-006-9017-8

Boddy, C. R. (2016). Sample size for qualitative research. *Qualitative market research: An international journal*, *19*(4), 426-432. https://doi.org/10.1108/qmr-06-2016-0053

Bonta, J., & Andrews, D. A. (2007). Risk-Need-Responsivity model for offender assessment and rehabilitation. *Rehabilitation*, *6*(1), 1–22.

Bonta, J., & Andrews, D. A. (2016). *The Psychology of Criminal Conduct* (6th ed.). Routledge. https://doi.org/10.4324/9781315677187

Bonta, J., & Wormith, J. (2007). Risk and need assessment. *Developments in Social Work with Offenders*, 131–152.

Bouffard, J. A., Mackenzie, D. L., & Hickman, L. J. (2000). Effectiveness of vocational education and employment programs for adult offenders. *Journal of Offender Rehabilitation*, *31*(1–2), 1–41. https://doi.org/10.1300/J076v31n01_01

Bowman, E. I., & Ely, K. (2020). Voices of returning citizens: a qualitative study of a supportive housing program for ex-offenders in a rural community. *The Prison Journal*, *100*(4), 423–446. https://doi.org/10.1177/0032885520939273

Braun, V., & Clarke, V. (2013). *Successful qualitative research: A practical guide for beginners*. SAGE Publications. https://www.torrossa.com/en/resources/an/5017629

Braver, S. L., MacKinnon, D. P., & Page, M. (2003). *Levine's guide to SPSS for analysis of variance*. Psychology Press. https://doi.org/10.4324/9781410607676

Brennan, T., Dieterich, W., & Ehret, B. (2009). Evaluating the predictive validity of the COMPAS risk and needs assessment system. *Criminal Justice and Behavior*, *36*(1), 21–40. https://doi.org/10.1177/0093854808326545

Burgess, E. W. (1936). Protecting the Public by Parole and by Parole Prediction. *Journal of Criminal Law and Criminology (1931-1951)*, *27*(4), 491–502. https://doi.org/10.2307/1137495

Cadigan, T. P., Johnson, J. L., & Lowenkamp, C. T. (2012). The re-validation of the federal pretrial services risk assessment (PTRA). *Federal Probation*, *76*(2), 3–9.

Campbell, M. A., French, S., & Gendreau, P. (2009). The prediction of violence in adult offenders: A meta-analytic comparison of instruments and methods of assessment. *Criminal Justice and Behavior*, *36*(6), 567–590. https://doi.org/10.1177/0093854809333610

Caudy, M. S., Durso, J. M., & Taxman, F. S. (2013). How well do dynamic needs predict recidivism? Implications for risk assessment and risk reduction. *Journal of Criminal Justice*, *41*(6), 458–466. https://doi.org/10.1016/j.jcrimjus.2013.08.004

Chu, C. M., Thomas, S. D. M., Ogloff, J. R. P., & Daffern, M. (2013). The short- to medium-term predictive accuracy of static and dynamic risk assessment measures in a secure forensic hospital. *Assessment*, *20*(2), 230–241. https://doi.org/10.1177/1073191111418298

Cohen, T. H., & Bechtel, K. (2017). Removal of the non-scored items from the post-conviction risk assessment instrument: An evaluation of data-driven risk assessment research within the federal system. *Federal Probation, 81*(2), 37-51.

Cohen, T. H., Lowenkamp, C. T., Bechtel, K., & Flores, A. W. (2020). Risk assessment overrides: Shuffling the risk deck without any improvements in prediction. *Criminal Justice and Behavior*, *47*(12), 1609–1629. https://doi.org/10.1177/0093854820953449

Cotter, R., Semisch, C., & Rutter, D. A. (2021). *Recidivism of federal offenders released in 2010*. United States Sentencing Commission. https://www.ussc.gov/sites/default/files/pdf/research-and-publications/research-publications/2021/20210930_Recidivism.pdf

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. SAGE Publications.

DeLisi, M., Elbert, M. J., & Drury, A. J. (2018). Federal criminal careers: An empirical examination of the post-conviction risk assessment (PCRA). *American Journal of Criminal Justice*, *43*(4), 792–809. https://doi.org/10.1007/s12103-018-9436-8

Desmarais, S. L., Johnson, K. L., & Singh, J. P. (2018). Performance of recidivism risk assessment instruments in U.S. correctional settings. In *Handbook of Recidivism Risk/Needs Assessment Tools* (pp. 1–29). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119184256.ch1

Desmarais, S. L., Zottola, S. A., Duhart Clarke, S. E., & Lowder, E. M. (2021). Predictive validity of pretrial risk assessments: A systematic review of the literature. *Criminal Justice and Behavior, 48*(4), 398–420. https://doi.org/10.1177/0093854820932959

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R. G., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., McClean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D., & Lautenbach, S. (2012). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, *36*(1), 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

Dowden, C., & Andrews, D. A. (2003). Does family intervention work for delinquents? Results of a meta-analysis. *Canadian Journal of Criminology and Criminal Justice*, *45*(3), 327–342. https://doi.org/10.3138/cjccj.45.3.327

Dowden, C., & Brown, S. L. (2002). The role of substance abuse factors in predicting recidivism: A Meta-analysis. *Psychology, Crime & Law*, *8*(3), 243–264. https://doi.org/10.1080/10683160208401818

Dyck, H. L., Campbell, M. A., & Wershler, J. L. (2018). Real-world use of the risk–need–responsivity model and the level of service/case management inventory with community-supervised offenders. Law and human behavior, 42(3), 258 –268. https://doi.org/10.1037/lhb0000279

Eaglin, J. B., Gilbert, S., Hooper, L., & Lombard, P. (1997). RPI profiles: Descriptive information about offenders grouped by their RPI scores. *Federal Judicial Center*, 1–24.

Farrington, D. P. (1986). Age and crime. *Crime and Justice*, *7*, 189–250. https://doi.org/10.1086/449114

Federal Bureau of Prisons. (n.d.). *BOP: About our agency*. United States Department of Justice. Retrieved February 9, 2023, from https://www.bop.gov/about/agency/

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *International journal of qualitative methods*, 5(1), 80-92. https://doi.org/10.1177/160940690600500107

Fitzgibbon, W., Hamilton, C., & Richardson, M. (2010). A risky business: An examination of Irish probation officers' attitudes towards risk assessment. *Probation Journal*, *57*(2), 163–174. https://doi.org/10.1177/0264550510362562

Fortune, C. A., & Heffernan, R. (2019). The psychology of criminal conduct: A consideration of strengths, weaknesses and future directions. *Psychology, Crime & Law*, *25*(6), 659–674. https://doi.org/10.1080/1068316X.2018.1560445

Franke, T. M., Ho, T., & Christie, C. A. (2012). The chi-square test: Often used and more often misinterpreted. *American Journal of Evaluation*, *33*(3), 448–458. https://doi.org/10.1177/1098214011426594

Gamst, G., Meyers, L. S., & Guarino, A. J. (2008). *Analysis of variance designs: A conceptual and computational approach with SPSS and SAS*. Cambridge University Press. https://doi.org/10.1017/cbo9780511801648

Garrett, B., & Monahan, J. (2019). Assessing risk: The use of risk assessment in sentencing. *Judicature*, *103*(2), 42–49.

Garson, G. D. (2016). Partial least squares. Regression and structural equation models.

Geller, A., & Curtis, M. A. (2011). A sort of homecoming: Incarceration and the housing security of urban men. *Social science research*, *40*(4), 1196-1213. https://doi.org/10.1016/j.ssresearch.2011.03.008

Gendreau, P., Little, T., & Goggin, C. (1996). A meta-analysis of the predictors of adult offender recidivism: What works! *Criminology*, *34*(4), 575–608. https://doi.org/10.1111/j.1745-9125.1996.tb01220.x

Gignac, G. E., & Szodorai, E. T. (2016). Effect size guidelines for individual differences researchers. *Personality and Individual Differences*, 102, 74-78. https://doi.org/10.1016/j.paid.2016.06.069

Gordon, H., Kelty, S. F., & Julian, R. (2015). An evaluation of the Level of Service/Case Management Inventory in an Australian community corrections environment. *Psychiatry, Psychology and Law*, *22*(2), 247-258. https://doi.org/10.1080/13218719.2014.941090

Graffam, J., Shinkfield, A. J., & Lavelle, B. (2014). Recidivism among participants of an employment assistance program for prisoners and offenders. *International Journal of Offender Therapy and Comparative Criminology*, *58*(3), 348–363. https://doi.org/10.1177/0306624X12470526

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis*, *11*(3), 255–274. https://doi.org/10.3102/01623737011003255

Gross, S. R., Possley, M., Otterbourg, K., Stephens, K., Paredes, J., & O'Brien, B. (2022). Race and wrongful convictions in the United States 2022. *U of Michigan Public Law Research Paper*, (22-051), 22-051. https://doi.org/10.2139/ssrn.4245863

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*(2), 293–323. https://doi.org/10.1037/1076-8971.2.2.293

Guest, G., MacQueen, K. M., & Namey, E. E. (2011). *Applied Thematic Analysis*. SAGE Publications. https://dx.doi.org/10.4135/9781483384436

Hannah-Moffat, K., Maurutto, P., & Turnbull, S. (2009). Negotiated risk: Actuarial illusions and discretion in probation. *Canadian Journal of Law and Society / La Revue Canadienne Droit et Société*, *24*(3), 391–409. https://doi.org/10.1017/S0829320100010097

Hanson, R. K., & Thornton, D. (1999). *Static 99: Improving actuarial risk assessments for sex offenders* (User Report No. 99–02). Department of the Solicitor General of Canada.

Hanson, R. K., & Thornton, D. (2000). Improving risk assessments for sex offenders: A comparison of three actuarial scales. *Law and Human behavior*, *24*(1), 119-136. https://doi.org/10.1023/a:1005482921333

Hansson, S. O., & Aven, T. (2014). Is risk analysis scientific? *Risk Analysis*, *34*(7), 1173–1183. https://doi.org/10.1111/risa.12230

Harris, P. M., Gingerich, R., & Whittaker, T. A. (2004). The "effectiveness" of differential supervision. *Crime & Delinquency*, *50*(2), 235-271. https://doi.org/10.1177/0011128703258939

Hart, S. D., Michie, C., & Cooke, D. J. (2007). Precision of actuarial risk assessment instruments: Evaluating the 'margins of error' of group v. individual predictions of violence. *The British Journal of Psychiatry*, *190*(S49), s60–s65. https://doi.org/10.1192/bjp.190.5.s60

Hastie, R., & Dawes, R. M. (2009). *Rational choice in an uncertain world: The psychology of judgment and decision making*. SAGE Publications.

Hay, C., Fortson, E. N., Hollist, D. R., Altheimer, I., & Schaible, L. M. (2007). Compounded risk: The implications for delinquency of coming from a poor family that lives in a poor community. *Journal of Youth and Adolescence*, *36*(5), 593–605. https://doi.org/10.1007/s10964-007-9175-5

Heller, S. B., Jacob, B. A., & Ludwig, J. (2010). Family income, neighborhood poverty, and crime. In P. Cook, J. Ludwig, and J. McCrary (Eds.), *Controlling crime: Strategies and tradeoffs* (pp. 419-459). University of Chicago Press. https://doi.org/10.7208/chicago/9780226115139.003.0010

Henwood, K. S., Chou, S., & Browne, K. D. (2015). A systematic review and meta-analysis on the effectiveness of CBT informed anger management. *Aggression and Violent Behavior*, *25*, 280–292. https://doi.org/10.1016/j.avb.2015.09.011

Hinton, P., McMurray, I., & Brownlow, C. (2014). *SPSS explained* (2nd ed.). Routledge. https://doi.org/10.4324/9781315797298

Ho, R. (2006). *Handbook of univariate and multivariate data analysis and interpretation with SPSS*. Chapman and Hall/CRC. https://doi.org/10.1201/9781420011111

Hunt, K. S., & Dumville, R. (2016). *Recidivism among federal offenders: A comprehensive overview*. United States Sentencing Commission.

IBM Strategic Assessment. (2004). *Strategic assessment: Federal probation and pretrial services system*, Administrative Office of the U.S. Courts.

Jarjoura, G. R., Triplett, R. A., & Brinker, G. P. (2002). Growing up poor: examining the link between persistent childhood poverty and delinquency. *Journal of Quantitative Criminology*, *18*(2), 159–188.

Johnson, J. L. (2017). Comparison of recidivism studies: AOUSC, USSC, and BJS. *Federal Probation*, *81*(1), 52–54.

Johnson, J. L., Lowenkamp, C. T., VanBenschoten, S. W., & Robinson, C. R. (2011). The construction and validation of the federal Post Conviction Risk Assessment (PCRA). *Federal Probation*, *75*(2), 16–29.

Kim, T. K. (2015). T test as a parametric statistic. *Korean Journal of Anesthesiology*, *68*(6), 540–546. https://doi.org/10.4097/kjae.2015.68.6.540

King, R., & Elderbroom, B. (2014). *Improving recidivism as a performance measure*. Urban Institute. Retrieved from http://hint-magazine.com/wp-content/uploads/2014/10/413247-improving-recidivism.pdf

Kirk, D. S. (2008). The neighborhood context of racial and ethnic disparities in arrest. *Demography*, *45*(1), 55-77. https://doi.org/10.1353/dem.2008.0011

Klingele, C. (2019). Measuring change: From rates of recidivism to markers of desistance. *Journal of Criminal Law & Criminology*, *109*(4), 769–817.

Koetzle Shaffer, D., Kelly, B., & Lieberman, J. D. (2011). An exemplar-based approach to risk assessment: Validating the risk management systems instrument. *Criminal Justice Policy Review*, *22*(2), 167–186. https://doi.org/10.1177/0887403410372989

Kornbrot, D. (2014). Point biserial correlation. In *Wiley StatsRef: Statistics Reference Online*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118445112.stat06227

Kraemer, H. C., Kazdin, A. E., Offord, D. R., Kessler, R., Jensen, P., & Kupfer, D. J. (1997). Coming to term with the terms of risk. *Archives of General Psychiatry*, *54*, 337–343. https://doi.org/10.1001/archpsyc.1997.01830160065009

Kroner, D. G., & Yessine, A. K. (2013). Changing risk factors that impact recidivism: In search of mechanisms of change. *Law & Human Behavior*, *37*(5), 321–336. https://doi.org/10.1037/lhb0000022

Latessa, E. J., Lemke, R., Makarios, M., & Smith, P. (2010). The creation and validation of the Ohio Risk Assessment System (ORAS). *Federal Probation*, *74*(1), 16–22.

Laub, J. H., & Sampson, R. J. (2001). Understanding desistance from crime. *Crime and Justice*, 28, 1-69. https://doi.org/10.1086/652208

Lewis-Beck, M. (1995). *Data analysis: An introduction*. SAGE Publications.

Løken, K. V., Mogstad, M., & Wiswall, M. (2012). What linear estimators miss: The effects of family income on child outcomes. *American Economic Journal: Applied Economics*, *4*(2), 1–35. https://doi.org/10.1257/app.4.2.1

Lombard, P., & Hooper, L. (1998). *RPI facts bulletin*. Federal Judicial Center.

Lovins, B. K., Latessa, E. J., May, T., & Lux, J. (2018). Validating the Ohio Risk Assessment System community supervision tool with a diverse sample from Texas. *Corrections*, *3*(3), 186–202. https://doi.org/10.1080/23774657.2017.1361798

Lowenkamp, C. T., Holsinger, A. M., & Cohen, T. H. (2015). PCRA revisited: Testing the validity of the Federal Post Conviction Risk Assessment (PCRA). *Psychological Services*, *12*(2), 149–157. https://doi.org/10.1037/ser0000024

Lowenkamp, C. T., Johnson, J. L., Holsinger, A. M., VanBenschoten, S. W., & Robinson, C. R. (2013). The federal Post Conviction Risk Assessment (PCRA): A construction and validation study. *Psychological Services*, *10*(1), 87–96. https://doi.org/10.1037/a0030343

Luallen, J., Radakrishnan, S., & Rhodes, W. (2016). The predictive validity of the Post-Conviction Risk Assessment among federal offenders. *Criminal Justice and Behavior*, *43*(9), 1173–1189. https://doi.org/10.1177/0093854816650481

Lurigio, A. J., Rollins, A., & Fallon, J. (2004). The effects of serious mental illness on offender reentry. *Fed. Probation*, *68*, 45.

Lutze, F. E., Rosky, J. W., & Hamilton, Z. K. (2014). Homelessness and reentry: A multisite outcome evaluation of Washington State's reentry housing program for high risk offenders. *Criminal Justice and Behavior*, *41*(4), 471-491. https://doi.org/10.1177/0093854813510164

Mair, G., Burke, L., & Taylor, S. (2006). 'The worst tax form you've ever seen'? Probation officers' views about OASys. *Probation Journal,* 53(1), 7-23. https://doi.org/10.1177/0264550506060861

Maruna, S. (2010). Mixed method research in criminology: Why not go both ways? In A. R. Piquero & D. Weisburd (Eds.), *Handbook of Quantitative Criminology* (pp. 123–140). New York, NY: Springer. https://doi.org/10.1007/978-0-387-77650-7_7

McCafferty, J. T. (2017). Professional discretion and the predictive validity of a juvenile risk assessment instrument: Exploring the overlooked principle of effective correctional classification. *Youth Violence and Juvenile Justice*, *15*(2), 103–118. https://doi.org/10.1177/1541204015622255

Mei, X., Hamilton, Z., Kowalski, M., & Kigerl, A. (2021). Redesigning the Central Eight: Introducing the M-PACT Six. *Youth Violence and Juvenile Justice*, *19*(4), 445–470. https://doi.org/10.1177/15412040211014264

Menard, S. (2002). *Applied logistic regression analysis* (2nd ed.). SAGE publications.

Mills, J. F., Kroner, D. G., & Hemmati, T. (2007). The validity of violence risk estimates: An issue of item performance. *Psychological Services*, *4*(1), 1-12. https://doi.org/10.1037/1541-1559.4.1.1

Monahan, J., & Skeem, J. L. (2014). Risk redux: The resurgence of risk assessment in criminal sanctioning. *Federal Sentencing Reporter*, *26*(3), 158–166. https://doi.org/10.1525/fsr.2014.26.3.158

Monahan, J., & Skeem, J. L. (2016). Risk assessment in criminal sentencing. *Annual Review of Clinical Psychology*, *12*(1), 489–513. https://doi.org/10.1146/annurev-clinpsy-021815-092945

Myers, D., Tosto, S., Amin, A., Jaroszkiewicz, P., & DiStasio, L. (2022). *An evaluation of federal reentry court in Connecticut*. Unpublished Manuscript. Henry C. Lee College of Criminal Justice and Forensic Sciences, University of New Haven.

Nahm, F. S. (2022). Receiver operating characteristic curve: Overview and practical use for clinicians. *Korean Journal of Anesthesiology*, *75*(1), 25–36. https://doi.org/10.4097/kja.21209

National Council on Crime and Delinquency. (2006). *Correctional Assessment and Intervention System*. https://evidentchange.org/assessment/correctional-assessment-and-intervention-system-cais/

Northpointe Institute for Public Management. (1996). COMPAS [Computer software].

Olds, D. L. (2008). Preventing child maltreatment and crime with prenatal and infancy support of parents: The nurse-family partnership. *Journal of Scandinavian Studies in Criminology and Crime Prevention*, *9*(sup1), 2–24. https://doi.org/10.1080/14043850802450096

Olver, M. E., Wong, S. C. P., Nicholaichuk, T., & Gordon, A. (2007). The validity and reliability of the violence risk scale-sexual offender version: Assessing sex offender risk and evaluating therapeutic change. *Psychological Assessment*, *19*(3), 318–329. https://doi.org/10.1037/1040-3590.19.3.318

Papalia, N., Spivak, B., Daffern, M., & Ogloff, J. R. P. (2019). A meta-analytic review of the efficacy of psychological treatments for violent offenders in correctional and forensic mental health settings. *Clinical Psychology: Science and Practice*, *26*(2), e12282. https://doi.org/10.1111/cpsp.12282

Park, H. M. (2009). *Comparing group means: T-tests and one-way ANOVA using Stata, SAS, R, and SPSS*. The Trustees of Indiana University. https://scholarworks.iu.edu/dspace/handle/2022/19735

Polaschek, D. (2012). An appraisal of the risk-need-responsivity (RNR) model of offender rehabilitation and its application in correctional treatment. *Legal & Criminological Psychology*, *17*(1), 1–17. https://doi.org/10.1111/j.2044-8333.2011.02038.x

Ramsey, R. J., & Frank, J. (2007). Wrongful conviction: Perceptions of criminal justice professionals regarding the frequency of wrongful conviction and the extent of system errors. *Crime & Delinquency*, *53*(3), 436–470. https://doi.org/10.1177/0011128706286554

United States District Court District of Connecticut. (2023). *Reentry Court*. https://www.ctd.uscourts.gov/reentry-court

Reisig, M. D., Holtfreter, K., & Morash, M. (2006). Assessing recidivism risk across female pathways to crime. *Justice Quarterly*, *23*(3), 384–405. https://doi.org/10.1080/07418820600869152

Reitz, K. R., & Klingele, C. M. (2019). Model penal code: Sentencing—Workable limits on mass punishment. *Crime & Justice*, *48*(1), 255–311. https://doi.org/10.1086/701796

Ruggero, T., Dougherty, J., & Klofas, J. (2015). *Measuring recidivism: Definitions, errors, and data sources*. Center for Public Safety Initiatives. https://www.rit.edu/liberalarts/sites/rit.edu.liberalarts/files/documents/our-work/2015-03%20-%20Measuring%20Recidivism%20-%20Definitions%2C%20Errors%2C%20and%20Data%20Sources.pdf

Sampson, R. J., & Laub, J. H. (2003). Desistance from crime over the life course. In *Handbook of the life course* (pp. 295-309). Boston, MA: Springer US.

Schwalbe, C. S. (2007). Risk assessment for juvenile justice: A meta-analysis. *Law and Human Behavior*, *31*(5), 449–462. https://doi.org/10.1007/s10979-006-9071-7

Serin, R. C. (2007). *The Dynamic Risk Assessment Scale for Offender Re-Entry (DRAOR)*. Unpublished scale. Carleton University, Ottawa, Ontario.

Silver, E., & Miller, L. L. (2002). A cautionary note on the use of actuarial risk assessment tools for social control. *Crime & Delinquency*, *48*(1), 138–161. https://doi.org/10.1177/0011128702048001006

Sims, R. L. (2000). *Bivariate data analysis: A practical guide*. Nova Science Publishers.

Singh, J. P., Desmarais, S. L., Hurducas, C., Arbach-Lucioni, K., Condemarin, C., Dean, K., Doyle, M., Folino, J. O., Godoy-Cervera, V., Grann, M., Ho, R. M. Y., Large, M. M., Nielsen, L. H., Pham, T. H., Rebocho, M. F., Reeves, K. A., Rettenberger, M., de Ruiter, C., Seewald, K., & Otto, R. K. (2014). International perspectives on the practical application of violence risk assessment: A global survey of 44 countries. *International Journal of Forensic Mental Health*, *13*(3), 193–206. https://doi.org/10.1080/14999013.2014.922141

Singh, J. P., Desmarais, S. L., Sellers, B. G., Hylton, T., Tirotti, M., & Van Dorn, R. A. (2014). From risk assessment to risk management: Matching interventions to adolescent offenders' strengths and vulnerabilities. *Children and Youth Services Review*, *47*, 1–9. https://doi.org/10.1016/j.childyouth.2013.09.015

Skeem, J. L., & Lowenkamp, C. T. (2016). Risk, race, and recidivism: Predictive bias and disparate impact. *Criminology*, *54*(4), 680–712. https://doi.org/10.1111/1745-9125.12123

Skeem, J. L., & Monahan, J. (2011). Current directions in violence risk assessment. *Current Directions in Psychological Science*, *20*(1), 38–42. https://doi.org/10.1177/0963721410397271

Skeem, J. L., Winter, E., Kennealy, P. J., Louden, J. E., & Tatar II, J. R. (2014). Offenders with mental illness have criminogenic needs, too: Toward recidivism reduction. *Law and human behavior*, *38*(3), 212-224. https://doi.org/10.1037/lhb0000054

Smith, P., Gendreau, P., & Swartz, K. (2009). Validating the principles of effective intervention: A systematic review of the contributions of meta-analysis in the field of corrections. *Victims & Offenders*, *4*(2), 148–169. https://doi.org/10.1080/15564880802612581

Stoltzfus, J. C. (2011). Logistic regression: A brief primer. *Academic Emergency Medicine, 18*(10), 1099–1104. https://doi.org/10.1111/j.1553-2712.2011.01185.x

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2013). *Using multivariate statistics* (Vol. 6, pp. 497-516). Pearson.

Tate, R. F. (1954). Correlation between a discrete and a continuous variable. Point-biserial correlation. *The Annals of Mathematical Statistics*, *25*(3), 603–607. https://doi.org/10.1214/aoms/1177728730

Taxman, F. S. (2018). Risk assessment: Where do we go from here? *Handbook of Recidivism Risk/Needs Assessment Tools*, 269–284. https://doi.org/10.1002/9781119184256.ch14

Taxman, F. S., Thanner, M., & Weisburd, D. (2006). Risk, need, and responsivity (RNR): It all depends. *Crime & Delinquency*, *52*(1), 28–51. https://doi.org/10.1177/0011128705281754

Terranova, V. A., & Ward, K. C. (2020). *Colorado pretrial assessment tool validation study final report* (pp. 1–97). The State of Colorado Office of State Planning and Budgeting and the University of Northern Colorado. https://www.nacdl.org/getattachment/18510570-e0eb-4d40-b737-5aafb30c1085/terranovaward_cpat-validation-study_final-report.pdf

Terry, G., Hayfield, N., Clarke, V., & Braun, V. (2017). Thematic analysis. In *The SAGE Handbook of Qualitative Research in Psychology* (pp. 17-36). SAGE Publications Ltd, https://doi.org/10.4135/9781526405555

Tibbetts, S. G., & Rivera, J. (2015). 11 prenatal and perinatal factors in the development of persistent criminality. In J. Morizot & L. Kazemian (Eds.), *The development of criminal and antisocial behavior: Theory, research and practical applications* (pp. 167–180). Springer. https://doi.org/10.1007/978-3-319-08720-7_11

Uggen, C., Wakefield, S., & Western, B. (2005). Work and family perspectives on reentry. *Prisoner reentry and crime in America*, 209-243. https://doi.org/10.1017/cbo9780511813580.008

United States District Court for the District of Connecticut. (2018). *ACT reentry court policy manual.* https://www.ctd.uscourts.gov/sites/default/files/Reentry-Court-Policy-Manual-3.21.18.pdf

United States Sentencing Commission. (2023). *Federal offenders in prison*. https://www.ussc.gov/research/quick-facts/federal-offenders-prison#:~:text=Punishment,imprisonment%20imposed%20was%20145%20months.

Van Horn, J., Eisenberg, M., Anne Souverein, F., & Kraanen, F. (2018). The predictive value of the central eight criminogenic risk factors: A multi-group comparison of dually diagnosed violent offenders with other subgroups of violent offenders. *Addiction & Addictive Disorders*, *5*(1), 1–11. https://doi.org/10.24966/AAD-7276/100014

VanBenschoten, S. (2008). Risk/needs assessment: Is this the best we can do? *Federal Probation*, *72*(2), 38–42.

Via, B., Dezember, A., & Taxman, F. S. (2016). Exploring how to measure criminogenic needs: Five instruments and no real answers. In F. S. Taxman (Eds.), *Handbook on risk and need assessment*: *Theory and practice* (1st ed., pp. 328–346). Routledge.

Viglione, J., Rudes, D. S., & Taxman, F. S. (2015). Misalignment in supervision: Implementing risk/needs assessment instruments in probation. *Criminal Justice and Behavior*, *42*(3), 263–285. https://doi.org/10.1177/0093854814548447

Walters, G. D. (1997). Predicting short-term release outcome using the LCSF and PICTS. *Journal of Mental Health in Corrections Consortium*, *43*(3–4), 18–25.

Walters, G. D. (2002). The Psychological Inventory of Criminal Thinking Styles (PICTS): A review and meta-analysis. *Assessment*, *9*(3), 278–291. https://doi.org/10.1177/1073191102009003007

Walters, G. D. (2012). Criminal thinking and recidivism: Meta-analytic evidence on the predictive and incremental validity of the Psychological Inventory of Criminal Thinking Styles (PICTS). *Aggression and Violent Behavior*, *17*(3), 272–278. https://doi.org/10.1016/j.avb.2012.02.010

Walters, G. D., & Cohen, T. H. (2016). Criminal thought process as a dynamic risk factor: Variable- and person-oriented approaches to recidivism prediction. *Law and Human Behavior*, *40*, 411–419. https://doi.org/10.1037/lhb0000185

Walters, G. D., & Lowenkamp, C. T. (2016). Predicting recidivism with the Psychological Inventory of Criminal Thinking Styles (PICTS) in community-supervised male and female federal offenders. *Psychological Assessment*, *28*, 652–659. https://doi.org/10.1037/pas0000210

Walters, G. D., & White, T. W. (1989). The thinking criminal: A cognitive model of lifestyle criminality. *Women Lawyers Journal*, *76*(2), 4–12.

Ward, T., Melser, J., & Yates, P. M. (2007). Reconstructing the Risk–Need–Responsivity model: A theoretical elaboration and evaluation. *Aggression and Violent Behavior*, *12*(2), 208–228. https://doi.org/10.1016/j.avb.2006.07.001

Wardrop, K. N. (2020). *A validation of the Dynamic Risk Assessment for Offender Re-entry (DRAOR) for use with offenders with mental disorder* (Doctoral dissertation, Carleton University). https://doi.org/10.22215/etd/2020-14117

Webster, C. D., Douglas, K. S., Eaves, D., & Hart, S. D. (1997). *HCR–20: Assessing risk for violence* (Version 2). Vancouver, BC, Canada: Mental Health, Law, and Policy Institute, Simon Fraser University.

Wehrman, M. M. (2010). Race, concentrated disadvantage, and recidivism: A test of interaction effects. *Journal of Criminal Justice*, *38*(4), 538–544. https://doi.org/10.1016/j.jcrimjus.2010.04.024

Wertz, M., Schobel, S., Schiltz, K., & Rettenberger, M. (2023). A comparison of the predictive accuracy of structured and unstructured risk assessment methods for the prediction of recidivism in individuals convicted of sexual and violent offenses. *Psychological Assessment*, *35*(2), 152–164. https://doi.org/10.1037/pas0001192

Wilderman, S., Hebert, R., Garvey, D., Lansing, M. E., Schack, R., Lopez A., & Friedman L., (2024). *State of reentry 2024*. Connecticut Department of Correction. https://ctnewsjunkie.com/wp-content/uploads/2024/02/2024-State-of-Reentry-Report-002-2.pdf

Wilpert, J., Van Horn, J. E., & Boonmann, C. (2018). Comparing the central eight risk factors: Do they differ across age groups of sex offenders? *International Journal of Offender Therapy and Comparative Criminology*, *62*(13), 4278–4294. https://doi.org/10.1177/0306624X18758899

Wormith, J. S. (2017). Automated offender risk assessment recidivism risk assessment: The next generation or a black hole? *Criminology and Public Policy*, *16*(1), 281–304. https://doi.org/10.1111/1745-9133.12277

Zhang, J., & Han, Y. (2022). Algorithms have built racial bias in the legal system-accept or not? *Advances in Social Science, Education and Humanities Research*, 1217–1221. https://doi.org/10.2991/assehr.k.220105.224