10-2014

Modifying The Criminalization Hypothesis: Predicting Jail Diversion Outcome With Clinical, Criminological, And Personality Factors

Wen Gu
Graduate Center, City University of New York

MODIFYING THE CRIMINALIZATION HYPOTHESIS:

PREDICTING JAIL DIVERSION OUTCOME WITH CLINICAL, CRIMINOLOGICAL, AND PERSONALITY FACTORS

By

Wen Gu

A dissertation submitted to the Graduate Faculty in Psychology in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2014

This manuscript has been read and accepted for the
Graduate Faculty in Psychology in satisfaction of the
Dissertation requirement for the degree of Doctor of Philosophy

Keith A. Markus

Date

Chair of Examining Committee

Maureen O'Connor

Date

Executive Officer

Keith A. Markus

Philip T. Yanos

Andrew A. Shiva

Supervisory Committee

THE CITY UNIVERSITY OF NEW YORK

Abstract

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Adviser: Professor Keith A. Markus

There are a disproportionate number of individuals with serious mental illness in the criminal justice system, compared to the general population. Mental health courts and jail diversion programs were developed to divert individuals with mental illness out of jails into community treatment to ease the overburden of treating psychiatric disorders in the criminal justice system. These programs have become increasing popular, but little is known about the characteristics of the diverted individuals that result in successful outcomes. The purpose of this study is to test different causal models of noncompliance as predicted by clinical, criminological, and personality variables, and examine the incremental validity of widely used clinical and risk assessment instruments over the screening instrument currently employed by diversion programs. Cox regression models do not support the strict interpretation of the criminalization hypothesis that treatment noncompliance is a result of clinical symptoms alone. Rather, treatment noncompliance is predicted by personality variables. Neither the Personality Assessment Inventory (PAI) nor the Violence Risk Appraisal Guide (VRAG) demonstrated incremental validity over the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) for predicting noncompliance. In addition, the PAI personality features, substance abuse, and aggression scales, were associated with all forms of treatment noncompliance.

ACKNOWLEDGMENTS

I am grateful to my advisor, Keith Markus, for his patience, thoroughness, encouragement, and guidance throughout my professional career. He not only cultivated my interests, but also equipped me with the tools to satisfy those curiosities. In addition, he gave me the freedom to pursue my interests and the space to overcome my struggles. I want to thank the faculty members on the admission committee of John Jay College and The City University of New York for providing me the opportunity to be a graduate student and training me to become a psychologist. They saw potential in me that I did not know I had and they put me in a position to succeed. I also thank my classmates Trevor Barese, Eugenia Garcia-Dubus, Thailyn Lopez, and Andrea Rodrigues, for their friendship and support throughout graduate school. Finally, this project would have not been possible without the assistance and support of Drs. Alexandra Garcia-Mansilla, Merrill Rotter, and the wonderful staff at Queens Treatment Alternative for Safer Communities.

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CHAPTER I

INTRODUCTION

Modifying the Criminalization Hypothesis: Predicting Jail Diversion Outcome with Clinical, Criminological, and Personality Factors

There are a disproportionate number of individuals with mental illness in jails and prisons, compared to the general population. Whereas the prevalence of individuals with serious mental illness (SMI) in the general population is approximately 5% (Kessler et al., 1996; Substance Abuse Mental Health Services Administration, 2008; United States Department of Health and Human Services, 1999; 2012), the prevalence of individuals with SMI in the forensic population is substantially higher at approximately 15% to 20% (Broner, Mayrl, & Landsberg, 2005; Ditton, 1999; Robins, & Regier, 1991; Steadman, Osher, Robbins, Case, & Samuels, 2009). A recent review of 28 studies between 1989 and 2013 across 16 states found that estimates of current and lifetime prevalence of SMI tended to be higher in state prisons but the estimates varied widely (Prins, 2014).

Although there is no consensus on the definition of SMI, the most widely used definition is: a mental, behavioral, or emotional disorder (excluding developmental and substance use disorders), currently or within the past year, to meet diagnostic criteria specified within the *Diagnostic and Statistical Manual of Mental Disorders - Fourth Edition - Text Revision* (DSM-IV-TR), that results in serious functional impairment that substantially interferes with, or limits, major life activities (National Institute of Mental Health, 2008). It includes major depression, schizophrenia, bipolar disorder, obsessive-compulsive disorder (OCD), panic disorder, posttraumatic stress disorder (PTSD), and borderline personality disorder (National Alliance of Mental Illness, 2004).

Approximately two million people are incarcerated in U.S. prisons or jails on any given day (Beck & Karberg, 2001), which leads to an estimate of approximately 283,000 inmates with mental illness (Ditton, 1999). The rate of SMI was significantly greater among female inmates (31%) than male (15%) inmates (Steadman et al., 2009). Furthermore, an estimated 38% to 52% of adults with SMI in the U.S. have been arrested at least once (Boccaccini, Christy, Poythress, & Kershaw, 2005; Holcomb & Ahr, 1988; McFarland, Faulkner, Bloom, & Hallaux, 1989; Silberberg, Vital, & Brakel, 2001). The Los Angeles County Jail, Chicago's Cook County Jail, and New York City's Rikers Island "each hold more people with mental illness on any given day than any hospital in the United States" (Council of State Governments, 2002).

The number of individuals with any mental illness diagnosis in the criminal justice system is substantially higher than the number of inmates with SMI. According to the U.S. Department of Justice, about 705,000 (56%) inmates in State prisons, 78,800 (45%) inmates in Federal prisons, and 479,900 (64%) inmates in local jails demonstrated mental health problems in 2005 (James & Glaze, 2006). A five-year census study of inmates with mental health problems in the New York State correctional systems found that male inmates who were involved with the public mental health system were 4 times more likely to be incarcerated than males in the general population (Cox, Morschauser, Banks, & Stone, 2001). As of 2004, 11% of prisoners, representing over 7,500 inmates with mental illness, were on the mental health caseload in New York State. Among those cases, nearly 3,000 individuals were in New York City jails (Department of Correctional Services, 2004). Rikers Island has essentially become New York State's largest psychiatric facility (Barr, 1999).

The following is an overview of factors that have contributed to the increasing prevalence of the mentally ill in the criminal justice system. The characteristics of defendants with mental illness are examined, in addition to why defendants with mental illness present as a major challenge for the both the correctional system and the mental health system. Three major hypotheses have been proposed to explain to increasing incarceration of the mentally ill. The development of the mental health courts and jail diversion was proposed as a solution, from a financial and efficacy perspective, to reduce the burden of treating mentally ill defendants in the correctional system without forfeiting public safety.

Deinstitutionalization

The U.S. encountered the problem of the mentally ill being overrepresented in jails and prisons in the 1800s, when Americans were shocked to find that many of the mentally ill individuals were housed in local jails and prisons (Torrey, Kennard, Eslinger, Lamb, & Payle, 2010). The large number of individuals with mental illness housed in jails and prisons and their poor care contributed to reforms to abolish the inhumane treatment of the mentally ill and improve the conditions of care championed by Dorothea Dix (Grob, 1966; Torrey et al., 1992). As a consequence of the reform, state mental hospitals were built with the revised beliefs and attitudes that mentally ill persons deserved to be treated, not punished. Data gathered between the 1880s and 1960s found comparatively low prevalence rates of mentally ill individuals in jails and prisons. A study conducted in the early 20th century found that less than 2% of arrestees were psychotic at the time of arrest, from a sample of 10,000 arrestees (Bromberg & Thompson, 1937). For nearly a century, the problem of overrepresentation of mentally ill individuals in jails and prisons appeared to have been solved. Individuals with mental illness were treated as patients in hospitals, not as criminals in jails or prisons.

The deinstitutionalization movement in the 1960s and 1970s has been identified as a major factor contributing to the overrepresentation of the mentally ill individuals in the criminal justice system (Barr, 1999; Lamb & Weinberger, 1998). Deinstitutionalization began as a well-intentioned attempt to improve the treatment and care of psychiatric patients by diverting them away from overcrowded and deteriorating state hospitals. Due to the development of psychotropic medication, socio-political movement preferring community treatment over inpatient hospitalization for the mentally ill, the passing of the Community Mental Health Act (1963) that funded community-based facilities that shifted the cost of services from the state level to the federal level, and the expansion of federal social welfare (i.e., Medicaid, Medicare, and Supplementary Security Income; Mechanic & Rochefort, 1990), 85% of patients from state psychiatric hospitals were discharged to the community (Torrey et al., 2010). The number of patients in state hospitals decreased from about 559,000 in 1955 to about 110,000 in 1985 (Mechanic & Rochefort, 1990).

Although deinstitutionalization is often considered one movement, it progressed at an uneven pace (Morrissey, 1989). The first phase occurred between 1956 and 1965 and consisted of opening state institutions to place new admissions and less impaired long-term patients in alternative settings, which revitalized some of the struggling state hospitals (Mechanic & Rochefort, 1990). The second phase, from 1966 to 1975, was a rapid downsizing of institutional capacity through massive patient discharges. This was done partially in reaction to economic difficulties and to avoid the expensive hospital improvement programs that new regulatory requirements required (Morrissey, 1989).

The depopulation of psychiatric facilities, in conjunction with more stringent criteria for civil commitment, a lack of proper community facilities, and inadequate treatment, coincided with an increase in the prevalence of the mentally in jails and prison populations (Engel & Silver, 2001; Fisher, Wolff, & Roy-Bujnowski, 2003; Lamb & Weinberger, 1998). Many discharged psychiatric patients became homeless or were arrested, resulting in repeated incarcerations (Schaefer & Stefanic, 2003). Inmates with mental illness were 2.5 times more likely to have experienced homelessness in the year prior to their arrest than inmates without mental illness (Ditton, 1999). Inmates with mental illness tend to serve longer sentences than inmates without mental illness. The average length of stay at Rikers Island for inmates without a diagnosed mental illness was 42 days, compared to the length of stay for inmates with a SMI of 215 days (Butterfield, 1998). As of 2000, in Pennsylvania, inmates with SMI were 3 times as likely to serve the maximum sentence, compared to inmates without SMI (Council of State Governments, 2002).

Since the mid-1970s, the rate of incarceration has increased dramatically, from 150 per 100,000 people in 1977 to 743 per 100,000 people in 2009 (Draine, 2003; Visher & Travis, 2003). Similarly, the proportion of mentally ill inmates in county jails and prisons has also increased substantially (Abramson, 1972). Arthur Bolton Associates (1976) found that approximately 7% of the inmates were psychotic after surveying more than 1,000 adult offenders in five California county jails; Swank and Winer (1976) found that 5% of inmates had a psychotic diagnosis after assessing 100 consecutive admissions in the Denver County Jail; Schuckit, Herrman, and Schuckit (1977) found that 5% of inmates had SMI in a Diego County jail; The 1978 national jail census study conducted by the USDOJ sampled 5,172 inmates in jails throughout the country and found that 4% of the male inmates and 6% of the female inmates reported a nervous disorder, 2% of male inmates and female inmates reported an emotional problem, and 1% of the male inmates and 2% of female inmates reported depression.

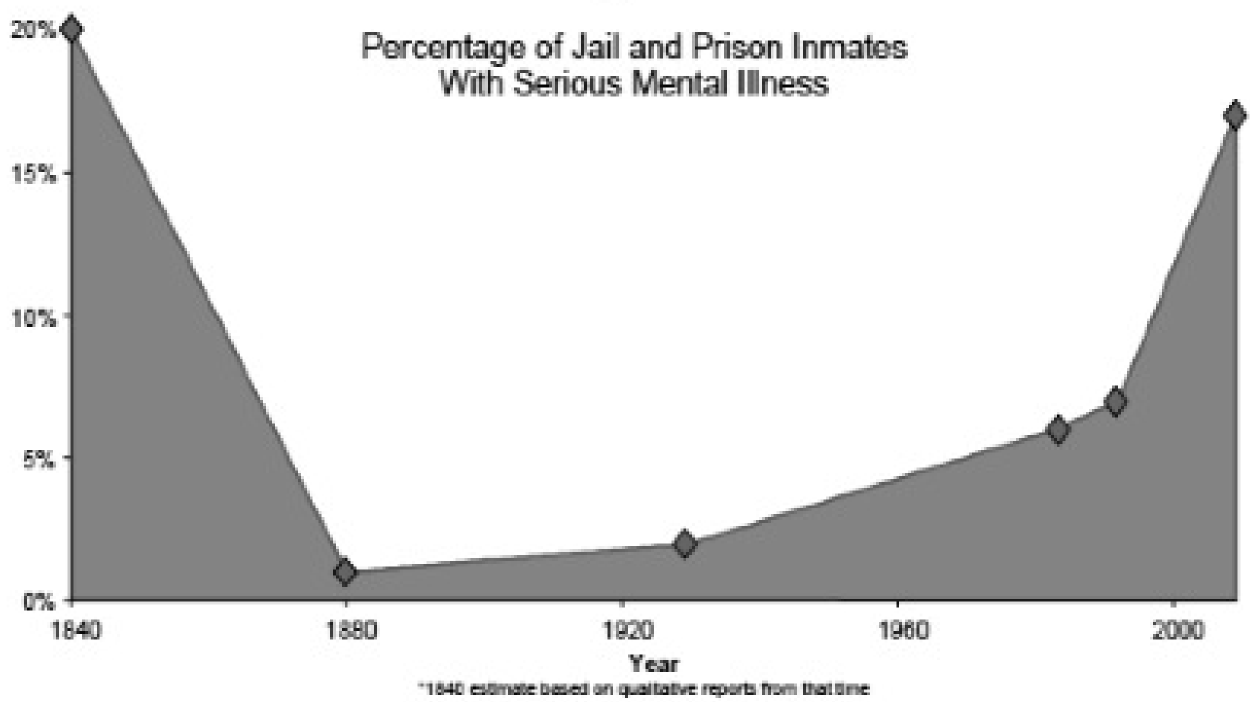
The problems worsened by the 1980s (Lamb & Grant, 1983). Epidemiological studies conducted by Teplin (1990, 1991) found that 6% of the inmates had a SMI at the time of admission in Chicago's Cook County Jail after assessing 728 randomly selected male inmates between 1983 and 1984. A jail survey sent to each of the 3,353 jails in the United States (U.S.) in 1992 reported that the average number of inmates with SMI was approximately 7%, ranging from 2% in Wyoming to 11% in Connecticut, Colorado, and Hawaii (Torrey et al., 1992).

By the late 1990s and early 2000s, the prevalence rate of individuals with SMI in jails and prisons were consistently in the double digits. A study conducted by the USDOJ in 1998 found that approximately 16% of inmates in jails and state prisons were categorized as having an SMI based on the self-report of symptoms or psychiatric admissions (Ditton, 1999). The American Psychiatric Association (2000) estimated that about 20% of inmates had SMI, with 5% of inmates being actively psychotic at any given time. The National Commission on Correctional Health Care issued a report to Congress, stating that approximately 18% of inmates in state prisons had a serious mental illness (Veysey, & Bichler-Robertson, 2002). Another survey conducted by the NSDOJ found that 24% of jail inmates and 15% of state prison inmates reported at least one symptom of a psychotic disorder (James & Glaze, 2006).

The most recent and methodologically rigorous study conducted by the Bureau of Justice Statistics found that approximately 17% of the 822 inmates housed in the five jails of New York and Maryland met criteria for SMI in the previous month using a structured diagnostic interview (James & Glaze, 2006). This overrepresentation of individuals with mental illness in the criminal justice system has once again translated into more mentally ill individuals being treated in the correctional system around the country than in psychiatric hospitals, which was not the intention of deinstitutionalization. The prevalence of individuals with SMI in the correctional system appears to be returning to the rates found in the 1840s (Figure 1).

Figure 1.

Percentage of Jail and Prison Inmates by Year



Models of Criminal Behavior

Three major explanations have been put forth to explain the overrepresentation of the mentally ill in the criminal justice system: the criminalization model, the criminological model, and the social/personality model. The following section summarizes each of the three explanations and the empirical evidence for each of the models. After the explanation of the three models criminal behavior, jail diversion programs are discussed as an approach to reduce the burden of treating defendants with mental illness in correctional settings and as a mean to examine the underlying causal mechanism of treatment noncompliance and recidivism. Jail diversion programs are also discussed in terms of their cost and outcomes.

Criminalization Model. The most widely touted explanation for the overrepresentation of the mentally ill in the criminal justice system is the criminalization hypothesis. The model presumes that individuals with mental illness, who would have been hospitalized prior to deinstitutionalization, are entering the criminal justice system as a result of untreated psychiatric symptoms (Torrey et al., 1992). The supposition is that deinstitutionalization, in conjunction with decrease in state hospital beds and poorly funded community treatment programs, resulted in increasing untreated mental illness that became criminalized. Markowitz (2006) found that a dramatic decline in the capacity of public psychiatric hospitals has a significantly negative impact on crime rate and arrest rate through its impact on the homeless population. His findings support the criminalization hypothesis that individuals with mental illness become entangled in the legal system because of inadequate mental health resources in the community and are arrested for psychosis-induced violence, disturbed behavior on the street, or "survival-type" crimes (Torrey et al., 2002).

The criminalization model posits a direct link between untreated mental illness and criminal behavior (Figure 2).

Figure 2.

The Criminalization Hypothesis

For example, individuals with substance use disorders are often arrested for substance-related crimes (e.g., drug possession, drug sale). Given that 64% of federal inmates with mental illness, 74% of state inmates with mental illness, and 76% of local jail inmates with mental illness have co-occurring substance use dependence or substance abuse (James & Glaze, 2006), individuals with mental illness are more prone to be entangled in the criminal justice system. The U.S. national policy on drugs also disparately affect individuals with mental illness, due to the high prevalence of co-occurring substance use disorders among the mentally ill (Kessler et al., 1996; Regier et al., 1990).

The criminalization model also attribute the increased arrests of individuals with mental illness to law enforcement agents responding punitively to aberrant behavior, such as irrational speech or behavior, inability to follow directions, and other psychiatric symptoms (Skeem & Bibeau, 2008). As evidence, the police rarely initiate psychiatric hospitalization for those who pose a danger to themselves or others (Teplin, 2000). In a sample of 506 arrests, the police arrested individuals with mental illness about twice as often as individuals without mental illness (47% vs. 28%) and attempted to initiate hospitalization for only 13% of mentally ill individuals (Teplin & Pruett, 1992).

There is, however, no consensus on the validity of the criminalization hypothesis. Strict interpretation of the criminalization hypothesis requires a causal link between untreated mental illness and criminal behavior. It presumes that once active mental illness is treated, the likelihood of incarceration decreases. However, there are data contrary to the causal mechanism underlying the criminalization hypothesis. Examining police reports of criminal offenses and the defendants' explanation for the offenses in a sample of 113 cases from the Hawaii jail diversion program, Junginger, Claypoole, Laygo, and Crisanti (2006) found that less than 10% of arrests were related to active mental illness symptoms and 26% of arrest were related to substance abuse. Similarly, 5% of the 220 parolees in Los Angeles, California were actively displaying psychotic symptoms at the time of their arrest, 2% of parolees were incarcerated for crimes related to being economically disadvantaged, but 90% of the parolees were for arrested for charges related reactive violence (Peterson, Skeem, Hart, Vidal, & Keith, 2010). This suggests that even among defendants with mental illness, there were few cases in which active clinical symptoms played a direct role in the arrests. In addition, the police officers were more likely to see psychotic behaviors as indicative of needing psychiatric treatment than arrests (Watson, Corrigan, & Ottati, 2004).

Researchers have generally found a weak relationship between psychosis and violence among all offenders (Bonta, Law, & Hanson, 1998; Quinsey, Harris, Rice, & Cormier, 2006). A meta-analysis of 204 studies found a small correlation between psychosis and violence (r = .16; OR = 1.53), but no meaningful distinction between violence and offenders with mental illness (r = .00; OR = 0.91) or violence with offenders without mental disorders (r = .01; OR = 1.27; Douglas, Guy, & Hart 2009). This finding is consistent with the types of crimes, for which individuals with mental illness are often arrested. The majority (51%) of federal inmates in 2010 were sentenced for drug offenses (Guerino, Harrison, & Sabol, 2012), and nearly half of the inmates with mental illness in prison were incarcerated for committing nonviolent crimes (National Alliance of Mental Illness, 2004).

Although the crime rate is elevated among individuals with mental illness, the overall percentage of individuals with mental illness who offend is in the single digits, after controlling for co-occurring substance abuse disorders (Swanson, 1994). Most studies do not find individuals with mental illness being arrested for more serious offenses (Hiday, 1999). Most people with mental illness are not violent, and most violent acts are not committed by people with SMI (Teplin, McClelland, Abram, & Wiener, 2005). In fact, people with SMI are at higher risk of being victims of violence than being perpetrators. Teplin et al. (2005) found that individuals with SMI are 11 times more likely to be victims of violent crime than the general population.

The risk assessment literature has also contributed evidence showing that individuals with mental illness can be managed in the community without substantial increases to risk in violence in the community. Following a sample of 951 patients from their psychiatric admission to one year after their discharge to examine patterns of violence among the mentally ill, the MacArthur Violence Risk Study dispelled many of the myths regarding the mentally ill and violence. Of the 951 patients, 689 (72%) did not have any violent incidents one year after discharge; within the 262 patients that had violent incidents, family members were the most at risk and most of the violent incidents occurred within the patients' homes. Approximately 30% of patients reported violent thoughts shortly after their hospitalization and the majority of the violence displayed by that sample occurred within the first 20 weeks of discharge. The likelihood of violence or other aggressive acts decreased noticeably after 20 weeks (Monahan et al., 2001). In addition, patients who did not have a co-occurring substance abuse disorder were no more likely to have a violent incident than the average person living in the same neighborhoods (Steadman et al., 1998). Although the rate of crimes was higher among individuals diagnosed with a mental illness, the percentage of those diagnosed with mental illnesses who offend remains very low (Monahan, 1997).

Among the clinical factors examined in relation to violence in the MacArthur study (i.e., diagnosis, psychopathy, delusions, hallucinations, violent thoughts, and anger problems), substances use (Silver, 2006) and psychopathy were moderately correlated with violence (Monahan et al., 2001). In fact, higher scores on the Hare Psychopathy Checklist – Screening Version (PCL-SV; Hart, Cox, & Hare, 1995) was the strongest predictor of future violence and added incremental predictive validity to other risk factors, including prior violence, criminal history, substance use, and personality disorders. In contrast, a diagnosis of schizophrenia was associated with lower rates of violence than other major mental illnesses; the presence of delusions did not predict higher rates of violence, even after controlling for the content of the delusions; hallucinations, including command hallucinations, did not elevate risk of violence, but command auditory hallucinations increased the likelihood of violence over the subsequent year was increased; non-delusional suspiciousness or a tendency to misperceive of others' behaviors and intentions as hostile appeared to have some link to subsequent violence (Arseneault, Moffitt, Caspi, Taylor, & Silva, 2000). Notably, any major clinical disorder was associated with lower rates of violence than a personality or adjustment disorder (Monahan et al., 2001). With respect to anger management, patients with high scores on anger during their hospitalization were twice as likely as those with low anger scores to engage in violent acts after discharge. However, the effect was not highly predictive and not clinically significant.

Criminological Model. The criminological hypothesis explains the overrepresentation of the mentally ill in the criminal justice system as a function of their position in the social hierarchy (Bonta et al., 1998). The link to crime and recidivism is not mental illness, but poverty. Fisher, Silver, and Wolff (2006) explained that people diagnosed with a mental illness engage in offending and deviant behaviors not because they have a mental disorder, but because they are poor. Their poverty constrains them socially and geographically, placing them at risk for engaging in many of the same behaviors displayed by those without mental illness who live in similar situations (Fisher et al., 2006). Poverty forces people to live in "settings that are rife with illicit substances, unemployment, crime, victimization, family breakdown, homelessness, health burdens, and a heavy concentration of other marginalized citizens" (Fisher & Drake, 2007, p.

546). The hypothesis posits poverty as the cause of criminal behavior and explains the higher prevalence of mental illness in criminal justice settings as a function of a worsening economy.

The lack of empirical evidence directly linking active symptoms to recidivism (Callahan & Silver, 1998; Monson, Gunnin, Fogel, & Kyle, 2001; Phillips et al., 2005) lends credence to alternative models to the criminalization hypothesis. General risk factors for crime, such as unemployment, poverty, homelessness, and substance abuse, are inherent in the social settings occupied by all individuals. A meta-analysis of 58 prospective studies of offenders with mental illness (70% with schizophrenia) found that clinical variables (e.g., diagnoses, treatment history) did not meaningfully predict a new general offense (r = -.02) or a new violent offense (r = -.03); the strongest predictors of a new violent offense (rs > .20) were antisocial personality, juvenile delinquency, criminal history, and employment problems (Bonta et al., 1998). These findings support the criminological hypothesis that those with mental illness offend because they are likely to have lower social economic status, which exposes them to risk factors and risky situations (Draine, Salzer, Culhane, & Hadley, 2002). That is, individuals with mental illness tend to live in disadvantaged neighborhoods, be unemployed, (Prins & Draper, 2009), abuse substances (Abram & Teplin, 1991; Abram et al., 2003), and associate with people who have criminal histories (Skeem, Eno Louden, Manchak, Vidal, & Haddad, 2008).

Although these variables have been linked with criminal behavior, the extent to which they play a causal role has not been established. The MacArthur study also found that living in dangerous neighborhoods where drugs and violence were prominent was a strong predictor for future violence, but that most people with mental illness were not violent (Monahan et al., 2001). Rather, most violent offenders were not mentally ill and the strongest risk factors for violence were shared among offenders with and without mental illness (Mulvey, 1994; Walsh, Buchanan,

& Fahy, 2002).

Social/Personality Hypothesis. The social/personality hypothesis explains the overrepresentation of the mentally ill in the criminal justice system as a function of adopting attitudes and thinking styles condoning or accepting of antisocial activities, and having criminal associates (Andrews, Bonta, & Wormith, 2006). The social/personality model postulates four major factors maintain ongoing criminal activity, including an established history of benefitting from criminal activity, a social environment that encourages and tolerates crime and criminals, personal attitudes and values supportive of criminal behavior, and a personality style that finds impulsive high-risk behavior rewarding (Bonta et al., 1998). Andrews et al., (2006) opined that the predictive validity of mental disorders for criminal justice involvement mostly consist of antisocial cognition, antisocial personality pattern, and substance abuse. As such, a third variable associated with mental illness, (e.g., adverse social environments), systematically increases exposure to modeling and reinforcement patterns that teach antisocial behavior.

Studies examining the cognitive style of persistent offenders generally support that specific cognitive biases (i.e., criminal thinking styles) contribute to repetitive criminal behavior (Walters, 1990). These biases include overconfidence in one's ability to evade arrest or sanctions (e.g. thinking one will never get caught despite evidence to the contrary) and a tendency to look for easy solutions to difficult problems and a sense of entitlement (Walters, 1990). Carr, Rosenfeld, Magyar, and Rotter (2009) found that thinking styles typically associated with criminality (i.e., mollification, entitlement, power orientation, and sentimentality) were found in a sample of civil psychiatric patients. In addition, psychiatric patients with correctional histories display attitudes and behaviors (i.e., intimidation, stonewalling, non-snitching) commonly associated with prisons (Rotter, McQuistion, Broner, & Steinbacker, 2005). They suggested that cognitive remediation strategies targeting these factors may reduce criminal activity in psychiatric patients.

The finding that individuals with mental illness and criminal justice involvement have disproportionate risk for offending, due to having even more general risk factors for recidivism than their relatively healthy counterparts (Bonta et al., 1998), is indirect evidence in support of the social/personality hypothesis. Based on a matched sample of 221 parolees with and without mental illness, Skeem et al. (2008) found that those with mental illness obtained significantly higher scores (g = .20) on the Levels of Services Inventory/Case Management Inventory (LS/CMI; Andrews, Bonta, & Wormith, 2004), particularly on the antisocial pattern subscale (e.g., early or diverse criminal behavior, criminal attitudes, pattern of generalized trouble). Similarly, based on a sample of 600 probationers, Girard and Wormith (2004) found that those with mental health problems (*n* = 169) obtained higher scores on the LS/CMI than those without such problems, and the LS/CMI predicted recidivism equally well for those with- and without- mental illness (Andrews et al., 2004; Girard & Wormith, 2004). In essence, these individuals may be a subset of both the clinical and correctional populations who have higher risk than either the clinical or correctional population alone for offending. However, there has been no direct investigations of whether disadvantaged environments or other variables increase exposure of those with mental illness to modeling and reinforcement patterns to internalize these risk factors, thus the social/personality hypothesis remains difficult to evaluate.

Literature Summary. Although three major hypotheses have been posited as three distinct explanations, the criminalization hypothesis appears to be the dominant explanation against which the other explanations have been framed. The criminological hypothesis and the social/personality may be potentially complementary rather than mutually exclusive, but they both refute the criminalization explanation. Consequently, evidence for either the criminological or social/personality hypotheses has been interpreted as evidence against the criminalization hypothesis.

Despite the lack of direct link between clinical symptoms and recidivism, the criminalization hypothesis remains viable because there is evidence that criminal behavior is directly attributable to mental illness for a small subgroup of offenders in the criminal justice system (Skeem, Manchak, & Peterson, 2011). Although Junginger et al. (2006) found that active symptoms were involved in very few arrests, active psychiatric symptoms still directly contributed to the arrests of some defendants. Similarly, Peterson et al. (2010) found that a minority (7%) of the mentally ill sample clearly fit the criminalization hypothesis, despite only 5% of parolees with mental illness manifested a pattern that was attributable to psychotic symptoms and only 2% fell in the disadvantaged or survival crime group. Even in the MacArthur Violence Risk Assessment study, 11% of violent behavior occurred while patients were delusional or hallucinating (Monahan et al., 2001). The criminalization hypothesis, therefore, remains an important component of any policy to address the overrepresentation of the mentally ill in the correctional system.

Nevertheless, any attempt to address the overrepresentation of the mentally ill in the correctional system cannot rely on treating clinical symptoms alone, thus alternative factors needs to be considered to the pure criminalization hypothesis. Empirical evidence suggests most people with mental illness are not violent, most violent offenders are not mentally ill, and the strongest risk factors for violence (e.g., past violence) are shared by offenders with and without mental illness (Monahan et al., 2001; Mulvey, 1994; Walsh, Buchanan, & Fahy, 2002). These are indirect evidence supporting the criminological and social/personality explanations.

The Risk-Need-Responsivity (RNR) model (Andrews, Bonta, & Hodges, 1990), which has been regarded as the premier model for guiding the assessment and treatment of defendants with mental illness (Andrews, Bonta, 2007; Mesler & Yates, 2007), acknowledges that clinical symptoms alone do not explain recidivism. The three core principles of the RNR model calls for matching the level of service to the defendant's risk for reoffending, targeting the criminogenic needs of the defendant, and tailoring the intervention to the abilities of the defendant. The eight dynamic criminogenic risk factors (i.e., family and/or marital factors, lack of education, poor employment history, lack of prosaically leisure activities, antisocial attitudes, antisocial friends and peers, antisocial personality pattern, substance abuse) essentially equate to the factors from the criminological hypothesis and the social/personality hypotheses mentioned above. The model applies cognitive social learning based interventions to target problematic thinking patterns and behaviors (Dowden & Andrews, 2004). Therefore, the pure interpretation of the criminalization hypothesis does not stand, and may need to be altered to better explain the phenomenon.

Jail Diversion Programs

The following section provides an overview of jail diversion programs as an approach to reduce the burden of treating defendants with mental illness in correctional settings. Jail diversion programs are discussed in terms of their cost, effectiveness, and eligibly.

The Problem. Individuals with mental illness who also have forensic histories are challenging for both clinical and criminal justice settings. From the perspective of the criminal justice system, mentally ill inmates place additional strain on an already overburdened criminal justice system that sees little meaning in applying punishment and deterrence for someone whose crime resulted, in many cases, from mental illness (Schaefer & Bloom, 2005). Police officers often do not make appropriate referrals of potential mentally ill patients for emergency services

(Steadman et al., 2001; Steadman, Morrissey, Braff, & Monahan, 1986; Way Evans & Banks, 1993), because many police referrals do not meet the threshold for dangerousness needed for involuntary treatment (Steadman, Braff, & Morrisey, 1988). In addition, police officers would rather do police work, like patrols, than spend time waiting in emergency rooms (Steadman et al., 2001). Mental health professionals may see patients with forensic histories as inappropriate for traditional treatment settings due to their perceived higher risk (Ryan, Brown, & Watanabe-Galloway, 2010). As the rates of incarceration surged from 100 to 450 per 100,000 people in the 1990s (Lamb & Weinberger, 1998), in conjunction with decreasing funding of state psychiatric institutions, these issues became more relevant for affected clients, for leadership in criminal justice and mental health systems, and for communities (Gilligan, 2001).

Incarcerated individuals with mental illness face complex and challenging needs that create additional instability and chaos in their lives. Jail and prisons were not created to be mental health hospitals, thus their staff and treatment services are not comparable to psychiatric hospitals (Kohl, 2000). Over 75% of inmates with psychiatric disorders have co-occurring substance abuse disorders (Broner, Borum, Whitmire, & Gawley, 2002; Teplin & Abram, 1991). Correctional settings have high incidences of violence and victimization, thus inmates with mental illness tend to be more vulnerable to violence because they may not be able to protect themselves (Wilkinson, 2000). They may inadequately cope with the additional stressors of being in jail or prison and develop psychiatric symptoms that make them more susceptible to victimization and segregation (Barr, 1999). Mentally ill inmates lose contact with their families and community mental health services. Individuals who received benefits, such as Medicaid, often lose them upon incarceration. Even for those who have completed their sentences, it is unlikely that benefits are restored immediately upon discharge from correctional facilities unless special efforts have been made to reapply for benefits during the pre-release phase. This further denies individuals the financial resources they need to survive in the community. The correctional experience has often both worsened individuals with mental illness as well as made it more difficult to obtain necessary mental health treatment in the community once these individuals return home (Carr et al., 2009; Rotter et al., 2005). Having a history of conviction and being labeled as a criminal may make community-based providers reluctant to treat some individuals. Therefore, the problems faced by those with mental illness often worsen after they are released from jail or prison (Barr, 1999).

The notion that incarceration is a poor alternative for individuals with mental illness is not novel. Asylums have existed since the 18th century worldwide. As the prevalence rate of the mentally ill continues to rise following the deinstitutionalization movement, mental health courts and jail diversion programs have been created to address the overrepresentation of the mentally ill in jail and prisons. To break this continuing cycling of mentally ill offenders through the criminal justice system, both the criminal justice system and mental health systems have advocated diverting offenders with mental illness from jails and prisons to community based mental health and social services (Steadman et al., 1999). Diversion programs attempt to achieve this goal by diverting appropriate defendants away from jails and prisons to an alternative sentence of mandatory treatment (Steadman et al., 1995). These programs typically screen defendants for the presence of mental disorder, employ mental health professionals to evaluate and negotiate with prosecutors, defense attorneys, community-based mental health providers, and the court to seek mental health dispositions as an alternative to prosecution as a condition of a reduction in charges or as satisfaction for charges (Steadman et al., 1999).

There are two different types of diversion programs, differentiated by where along the legal process diversion occurs. Pre-arrest or *prebooking* diversion programs typically focus on police officers, who are often the first point of contact with individuals with mental illness in the community. Since the initial interactions and actions with persons with mental illness are so critical to determining the situation's outcome, pre-arrest jail diversion strategies rely heavily on police becoming knowledgeable about the nature of mental illness, de-escalating crisis situations and providing options for mental health treatment alternatives to incarceration that are available in the community. Pre-arrest strategies include: police training to recognize the mental illness; deployment of a mobile crisis response team that provide assistance and support to the police and the individual; and transportation of the individual to mental health treatment rather than jail. Because diversion occurs earlier in the legal process and functions as a preventive measure ideally, individuals with mental illness tend to be connected with treatment sooner and do not make it the later legal actions. Post-arrest or *post-booking* diversion programs are more common and attempt to divert defendants after charges have been filed. There is a more thorough process of evaluating individuals to determine the presence of mental illness and negotiating with prosecutors, attorneys, mental health courts and treatment providers to dispose of the case without additional jail time, and link the individual with mental health treatment as a condition of a reduction in charges, deferred prosecution, or in place of prosecution.

In the past two decades, jail diversion programs have increased in the U.S. from 52 in the 1990s to over 400 in 2013 (Steadman & Barbera, 1994; Steadman & Naples, 2005; Substance Abuse and Mental Health Services Administration, 2013). Since, the first official mental health court in the U.S. was formed in 1997 in Broward County, 43 states have since created at least one mental health court (Redlich, Steadman, Monahan, Robbins, & Petrila, 2006; Substance

Abuse and Mental Health Services Administration, 2013). Although most diversion programs operate through the specialized mental health courts, some also work within regular criminal courts. These diversion programs attempt to divert defendants into treatment programs as soon as possible after the arrest. They seek to not only decrease psychopathological symptoms by placing defendants in appropriate treatment, but also create stability by improve the quality of life of defendants, decreasing homelessness, decreasing problematic behaviors (e.g., aggression), have regular contact with treatment providers, which all lead to decreasing instances of hospitalization and incarceration. Although many diversion programs initially only accepted defendants charged with non-violent offenses, some of the more recently created mental health courts also attempt to divert the defendants charged with more serious offenses (Redlich, Steadman, Monahan, Petrila, & Griffin, 2005).

Rising Cost. Jail diversion programs not only make sense clinically, but also financially. Incarceration is expensive and the cost of maintaining inmates in correctional facilities has risen steadily. According to the Bureau of Justice Statistics, in 2001 the average annual cost per state inmate was $22,650 and per federal prisons was $22,632; Cost varied by state, ranging from $8,128 per inmate in Alabama to $44,000 per inmate in Maine (Stephan, 2004). By 2007, the average cost per inmates was around $34,003 per inmate, ranging from $10,162 per inmate in Mississippi to $100,229 per inmate in Massachusetts (The Pew Center on the States, 2008). At the pinnacle of the prison population in 2009, the annual spending on a single inmate ranged from approximately $18,000 in Mississippi to approximately $50,000 in California (The Economist, 2010). The most recent statistics on the cost of maintaining inmates by the VERA Institute of Justice show that as of 2010, the annual cost per inmate was $31,286, ranging from $14,603 in Kentucky to $60,076 in New York (Henrichson & Delaney, 2012).

The rising cost of incarcerations is partially driven by the different treatment needs of mentally ill defendants, including additional mental health staffing, psychiatric medications, and psychiatric evaluations (Torrey et al., 2010). When a defendant with suspected mental illness is arrested, psychiatric examinations are necessary, which costs over $2,000 each time (Torrey et al, 2010). In Broward County, Florida, it cost $80 per day to house a regular inmate but $130 per day for an inmate with mental illness; In Texas prisons, the average prisoner costs the state approximately $22,000 annually, but mentally ill prisoners cost between $30,000 to $50,000 annually (Bender, 2003; Miller & Franz, 2007). In Ohio's Clark County Jail, psychiatric medication costs exceeded the food costs of inmates (Gottschlich & Cetnar, 2002).

Proponents of jail diversion programs argue that diverting mentally ill defendants for treatment in the community makes sense financially, because the cost of treatment defendants in inpatient psychiatric hospitalizations or correctional systems are considerably higher than those of outpatient services. Phillip and Burns (2002) estimated that an Assertive Community Team (ACT) program, which is a type of community mental health treatment with a multidisciplinary team that sees a patient 6 times monthly, costs approximately $9,000 to $12,000 per year per person. Jail diversion programs benefit both the defendants and the systems they enter, as those who are diverted are expected to benefit from access to treatment and symptom stabilization, which should lead to reductions in arrests, hospitalizations, and the need for services from the criminal justice and emergency mental health systems (Cosden, Ellens, Schnell, Yasmeen, & Wolfe, 2003; Steadman et al., 1999). The few existing studies that examine the cost-effectiveness of jail diversion programs suggest they are generally more cost-effective than treating defendants in custodial settings, especially if the programs are run through not-for-profit organization than through the court system. Comparing the financial resources utilized by diverted individuals with non-diverted individuals in nine diversion programs across four counties, Cowell, Broner and Dupport (2004) found that diversion programs in Lane County, Oregon saved nearly $1,796 per person; Memphis, Tennessee saved nearly $5,855 per person; New York City, New York saved $6,260 per person. Only one diversion program in Tucson, Arizona cost $447 more per person than treatment in custodial settings. However, due to diversion programs being fairly new, there being different models of diversion in different communities, and different resources in the correctional system of a given state, direct comparison of cost among diversion programs nationwide remains difficult.

Outcomes. Offenders who were diverted generally have better clinical and public safety outcomes than those who were not. Once diverted, individuals with an index arrest for minor crimes – that is, higher-level misdemeanors and low-level felonies – have fewer days of subsequent incarceration (Hoff, Baranosky, Buchanan, Zonana, & Rosenheck, 1999). In addition, individuals charged with violent crimes fared no worse than those charged with nonviolent crimes, although the defendants who had committed violent crimes were less often approved for participation in diversion (Naples & Steadman, 2003).

Draine, Blank, Kottsieper and Solomon (2005), comparing the effectiveness of jail diversion program with in-jail mental health treatment, found that the two programs served slightly different subpopulations. The defendants who were recruited for diversion had more acute psychiatric symptoms and were more likely to have a psychotic diagnosis, whereas defendants who received in-jail mental health services were more likely to have been on probation or parole in the past and to have received substance abuse treatment. Draine et al. (2005) argued that jail diversion and in-jail mental health treatment may not be different treatment alternative, but rather complementary services that serve different segments of the forensic population. However, being eligible for diversion is not the only legal option a defendant may have and does not guarantee that the defendant agrees or consents to diversion, thus there may be discrepancies between the two samples.

Comparing the outcomes of four mental health jail diversion programs in California, Minnesota, and Indiana, Steadman, Redlich, Callahan, Robbins, and Vesselinov (2011) found that diverted defendants, compared to the defendants who received the treatment-as-usual, met the public safety goals of lowering arrest rates (49% vs. 58%) and days of incarceration (82 days vs. 152 days) at 18 months post-treatment, and that both clinical and criminal justice factors were associated with better public safety outcomes. The results of this study were especially compelling due to the stringent method of ensuring the mental health courts included in the study were from jurisdictions that had sufficient defendants in the treatment-as-usual condition.

One survey, asking the directors of diversion programs about their attitudes towards diversion and the perceived effectiveness of the programs, found that most directors thought the program was effective (Steadman et al., 1994). Another study found that court-mandated treatment programs were more effective for defendants who were seriously mentally ill compared to a group that were released to treatment but who were not mandated to receive regular court follow-ups (Lamb, Weinberger, & Reston-Parham, 1996). A retrospective study examining the effectiveness of one jail diversion program in a New England city between 1994 and 1997, found that diversion effectively reduced incarceration days among defendants with substance abuse disorders and defendants with dual diagnoses in the year following the index offense, but diversion significantly reduced jail time only among those who were arrested for the more serious minor offenses that were associated with longer jail sentences (Hoff, et al., 1999).

Shafer, Arthur, and Franczak (2004) found that among the 248 defendants with dual diagnoses in Arizona who were recruited for jail diversion improved on measures of mental health, substance use, physical health, criminality, and housing one year after the index offense, compared to 90 days prior to the offense. Although the overall re-arrest rate was similar between diverted and non-diverted defendants statistically significantly lower rates of re-arrest were found for defendants charged with lower level misdemeanor crimes, compared to their non-diverted counterparts (Shafer et al., 2004).

Eligibility. Not every incarcerated individual with mental illness is eligible for diversion. Mire, Forsyth, and Hanser (2007) conveyed that identifying the defendants who are most open to therapeutic services and motivated for treatment, matching the defendants and the mental health professional who provides therapeutic services, and ensuring quality continuity of care of mental health services affect successful diversion. Examining 34,832 activities made by 20 jail diversion programs in the U.S. that resulted in diversion decisions, Naples and colleagues (2007) found that approximately 6% of cases examined by the mental health courts were referred for diversion, and 65% of the referred cases were accepted for jail diversion. The authors argued that both formal and informal factors influenced decision-making regarding diversion and that a tremendous amount of activities occurred early in each court case to enroll a small number of defendants in diversion.

Overall, the individuals referred to diversion programs tended to be females, Caucasians, and were older, and a lower proportion of felony and violence charges (Steadman et al., 2009). In addition, women and individuals charged with less serious crimes were more likely to be accepted for diversion (Naples et al., 2007). Luskin (2001) found that having a history of felony convictions, a current charge of a crime against a person, and being male decreased chances for diversion in one court-based diversion program. In addition, there was an age by gender interaction, such that older males and younger females were more likely to be diverted. Although Luskin (2001) interpreted the interaction as youth signaling danger for men but not for women, it could also be the result of selection bias in the mental health courts. Diverted defendants were more likely to have indicators of better mental health, higher life satisfaction, and were less likely to have been previously arrested or to have spent prior time in jail (Broner et al., 2004). Examining case processing in seven mental health courts, Steadman and colleagues (2005) found that there was bias in decision-making at the referral point, but not at the decision point, to accept or reject defendants.

Although most of the research on diversion programs suggests they promote positive outcomes, an examination of the rediversion rates, or the diversion of an individual for a second offense, found that approximately 20% of defendants who were diverted were rediverted at least once and that nearly 50% of those who experienced rediversion were rediverted within 90 days of their initial diversion (Boccaccini, Christy, Poythress, & Kershaw, 2005). There appears to be a subset of defendants who were diverted multiple times and required a higher amount of resources.

Jail diversion programs have increased in popularity since their inception, but there have been few studies that compare the effectiveness of jail diversion programs across communities. Several difficulties exist with comparing diversion programs across different states and communities. First, jail diversion is still a fairly new concept and not available in every state and local community. Second, different models of jail diversion make them difficult to compare geographically. Whereas pre-arrest diversion occurs earlier in the legal process, post-arrest diversion undergoes a more thorough of screening and negotiations. Even within post-arrest diversion programs, different states and communities may have different eligibility criteria. For example, some mental health courts may only hear cases involving persons with mental illness who have been charged with non-violent crimes, whereas others divert a wider range of cases. In addition, some diversion programs may have different attitudes toward working with defendants with higher levels of risk and accept defendants who are most likely to succeed for diversion.

Jail diversion may not be appropriate for defendants based on legal grounds as well. Accepting a plea for jail diversion requires the defendants to plead guilty to the highest index charge, thus it exposes defendants to a potentially more severe penalty. The exposure to a potentially more severe legal sanction raises the question of how competent defendants are to make that decision and how much they appreciate the legal ramifications for not complying with the treatment mandate. Although the defendants are informed about the treatment process with guidance from their attorney, defendants could potentially be in a position, in which they wind up spending more time under a court mandate than had they entered into a plea-bargain for a lesser charge. Redlich, Hoover, Summers, and Steadman (2010) found that among a sample of 200 newly enrolled defendants at two diversion programs, over 95% of the defendants understood there would be regular follow-up with the court, but about 34% of the defendants reported not to have been told that diversion was voluntary or told of the requirements prior to entering, and 27% of the defendants demonstrated clinically impaired legal competency. Some defendants may not be ideal for a jail diversion disposition because the risk of their failing the treatment mandate not only results in a worse legal outcome, but they will less likely be referred for another diversion opportunity. Due to the complexity of taking such a plea, it is important that defendants are evaluated for appropriateness for diversion for both clinical and legal reasons. For example, individuals who are not U.S. citizens may have their immigrations status negatively affected by having a felony conviction, if they were to fail the treatment mandate.

Summary. Although few studies have attempted to evaluate the effectiveness across states and communities due to aforementioned difficulties, they generally show that individuals with mental illness who were diverted generally have better outcome than those who were not diverted at one-year follow-up, with respect to fewer clinical symptoms, lower recidivism, and lower treatment cost. Some studies hinted that diversion programs could be expanded in scope. Naples and Steadman (2003) showed that using index crime severity to determine diversion eligibility may not be appropriate, because individuals charged with violent crimes fared no worse than those charged with nonviolent crimes, even though those who had committed a violent crime were less often approved for participation in diversion. In addition, given that most crimes committed by individuals with mental illness are non-violent, property and substance-related offenses, using index crime severity as an eligibility criterion may not be too relevant for diversion purposes. Although diversion programs primarily diverted individuals with substance use programs in its inception, they have now expanded to divert defendants who commit other types of offenses.

Mental health diversion programs began nearly 30 years ago to ease the burden of treating overwhelming number of defendants with mental illness in jails and prisons. These programs sought to identify mentally ill defendants and to link them to treatment programs in the community, rather than incarcerate them (Steadman et al., 1999). Jail diversion programs have increased in popularity in the last decade, increasing from 52 programs in 1992 (Steadman, Morris, & Dennis, 1995) to over 400 (Substance Abuse and Mental Health Services Administration, 2013) and appear to be effective, yielding positive outcomes at 1-year follow-up. However, because the creation of diversion programs were driven by practical and financial needs (Steadman, Davidson & Brown, 2001), these programs were not based on empirical evidence of success and contained a number of flaws. Few diversion programs conduct formal risk assessment evaluation with empirically supported risk assessment instruments both to screen defendants for diversion and prior to releasing mentally ill defendants back to the community. The states and counties that use risk assessment instruments tend to use specialty instruments, many of these measures have not undergone the rigors of independent study and validation of results published in peer-reviewed journals. In essence, little is known about the clinical characteristics of the diverted individuals that result in successful outcomes or the validity of risk assessment instruments for community diversion or predicting successful diversion.

Purpose and Rationale for the Current Study

The purpose of this study is to address this gap in the literature by identifying psychological, criminological, and social/personality factors that lead to successful diversion, examining the incremental validity of widely used clinical and risk assessment instruments, compared to the screening instruments currently used by diversion programs, and exploring profiles that predict various types of treatment noncompliance. At present, diversion programs appear to be adopting the “kitchen sink” approach, namely targeting any and all explanatory variables for why individuals with mental illness may engage in criminal behavior. Given that diversion programs have limited resources and can only divert a small proportion of defendants, a closer examination of psychological characteristics that lead to successful diversion may enable diversion programs to better screen defendants and dedicate resources. The following section articulates the three goals in more detail, along with the hypotheses for each respective goal.

CHAPTER II

Method

Sample

The sample consists of defendants who were referred for evaluations to determine eligibility for mental health diversion to the Queens Treatment Alternatives for Safer Community (TASC) Mental Health Diversion Program. TASC is a not-for-profit criminal justice agency that receives funding through the New York State Department of Probation and Correctional Alternatives, New York City Council, the New York State Division of Criminal Justice Services (DCJS), and federal agencies. Working in collaboration with the District Attorney's office and the Mental Health Court, TASC provides an in-depth diagnostic evaluation of the defendants and identify appropriate treatment resources that can meet the needs of the offenders. The program attempts to prevent repeat criminal activity and re-arrest by assessing, referring to treatment, and monitoring the progress of mentally ill individuals in the Queens criminal justice system. It is authorized to divert appropriate defendants who are bound for jail or state prison into drug and/or mental health treatment programs. It is a post-arraignment diversion program that diverts defendants charged with both felonies and misdemeanors to mental health and substance abuse treatment programs. Although the majority of the defendants accepted by TASC for diversion occur through the mental health court, TASC also monitors defendants who are diverted in other courts.

The referred defendants are evaluated and screened for diversion eligibility, which included a major mental illness diagnosis that results in serious functional impairments. Eligible defendants enter a conditional guilty plea, are placed in treatment, and their treatment progress is monitored by TASC. Sentencing is deferred until success or failure under the mandate according to guidelines agreed upon prior to the plea. Successful completion of the mandate usually yields a conviction of a lesser charge and possible non-jail sentence; failure yields sentencing to a jail sentence agreed upon prior to the plea. Court mandated treatments are typically 9-months for misdemeanor cases and 1-year for felony cases.

Among the 135 defendants referred for diversion for this study, 84 (62%) were from archival data and 51 (38%) cases were newly collected. Eighteen defendants in this sample were evaluated prior to 2010. Therefore, at most, 13% of the sample may have overlapped with the sample reported in Barber Rioja (2009). Among the referred 135 defendants, 27 defendants were rejected due to ineligibility (i.e., no major mental illness diagnosis) or were considered too high risk, and 10 defendants withdrew their applications from the Queens TASC Mental Health Diversion Program and took alternative dispositions. Therefore, outcome data were available for the 98 defendants who were accepted for diversion.

The sample of 98 defendants who accepted legal dispositions through Queens TASC Mental Health Diversion Program were similar in demographics to the entire sample of referred defendants, with the exception of psychiatric diagnosis (Table 1).

Table 1.

Demographics of Defendants Referred and Accepted for Diversion

	Referred (*N* = 135)		**Accepted (*N* = 98)**		
Variable	***M***	***SD***	***M***	***SD***	***d***
Age (Years)	33.34	12.82	33.16	12.64	-0.01
Years of Education	12.17	2.16	12.19	2.23	0.01
Prior Arrests	3.08	5.25	2.69	5.05	-0.08
Prior Convictions	1.76	3.66	1.54	3.41	-0.06
Age at First Offense (Years)	25.49	10.98	25.18	10.35	-0.03

	Frequency	%	Frequency	%	
Gender					-0.01
Male	105	77.8	76	77.6	
Female	30	22.2	22	22.4	
	Frequency	***%***	***Frequency***	***%***	
Marital Status					-0.03
Singe	87	64.4	63	43.9	
Married	16	11.9	22	11.2	
Divorced	9	6.7	7	7.1	
Separated/Widowed	23	17.0	17	17.3	
	Frequency	***%***	***Frequency***	***%***	
Race/Ethnicity					-0.05
Caucasian	59	43.7	43	43.9	
African American	40	29.6	25	25.5	
Hispanic	22	16.8	18	18.4	
Asian	10	7.4	9	9.2	
Other	4	3.0	3	3.1	
	Frequency	***%***	***Frequency***	***%***	
Charge					0.02
Felony	98	72.6	72	73.5	
Misdemeanor	37	27.4	26	26.5	
	Frequency	***%***	***Frequency***	***%***	
Prior Psychiatric Treatment					-0.04
No	31	23.0	19	19.4	
Yes	99	73.3	77	78.6	
Unsure	5	3.7	2	2.0	
	Frequency	***%***	***Frequency***	***%***	
Prior Drug Treatment					-0.05
No	62	45.9	41	41.8	
Yes	67	49.6	54	55.1	
Unsure	6	4.4	3	3.1	
	Frequency	***%***	***Frequency***	***%***	
Primary Diagnosis					0.44*

Psychotic Disorder	29	21.5	26	26.8
Major Depressive Disorder	25	18.5	25	25.5
Bipolar Mood Disorder	25	18.5	20	20.4
Anxiety-Related Disorder	17	12.6	15	15.3
Substance-Related Disorder	15	11.1	9	9.2
Personality Disorder	2	1.5	3	3.0
None	22	16.3	0	0.0

Note. *d* = Cohen's d. Calculations of Cohen's d with nominal data were done using formulas from (Lipsey & Wilson, 2000) and the Campbell Collaboration.
*$p < .05$.

The difference in psychiatric diagnosis was expected between the defendants who were accepted for diversion and defendants who were not because the defendants who do not have a psychiatric diagnosis were not eligible for mental health diversion through TASC.

The current sample differs notably in composition compared to the sample of 61 defendants reported in Barber-Rioja (2009), which also included defendants from the Queens TASC Mental Health Diversion Program. The current sample is on average younger in age (33 years vs. 39 years), contains more males (78% vs. 69%), more Caucasians (44% vs. 7%), fewer African Americans (28% vs. 51%), fewer Hispanics (15% vs. 26%), and has more education (12 years vs. 10 years). In addition, fewer defendants in this sample had a prior criminal history (59% vs. 90%), prior mental health treatment (71% vs. 97%), and prior substance use treatment (50% vs. 93%). These differences could be attributed to the current data being collected from one diversion program from 2009 to 2014, whereas the sample recruited in Barber Rioja (2009) was from four diversion programs in three separate counties in New York City within one year. The current sample is more representative of the ethnic diversity of Queens County, whereas the sample from Rioja (2009) was more representative of the higher ethnic minority demographic compositions of the Bronx and Brooklyn. In addition, approximately 65% of the sample in

Barber Rioja (2009) was recruited from one program in Brooklyn, EAC LINK, which included clients who were not mandated to treatment.

Measures

This study uses three measures: The Correctional Offender Management Profiling for Alternative Sanctions (COMPAS; Brennen & Oliver, 2000), the Personality Assessment Inventory (Morey, 1991, 2007) and the Violence Risk Appraisal Guide (VRAG: Quinsey, Harris, Rice, & Cormier, 2006).

COMPAS Core. The Correctional Offender Management Profiling for Alternative Sanctions (COMPAS; Brennen & Oliver, 2000) is a statistically based risks-and-needs instrument designed to assess key risk and needs factors in correctional populations and to provide decision-support for criminal justice professionals when placing offenders into the community. The COMPAS is delivered in a structured-interview format and calculates a criminogenic and needs profile for each defendant with respect to criminal history, needs assessment, criminal attitude, social environment, socialization failure, criminal opportunity, criminal personality, and social support (Brennan & Oliver, 2000). The COMPAS has a number of assessment modules tailored to the purpose of assessment (e.g., Reentry, Pretrial, Youth). The current study only used the core assessment module, which examines the retrospective risk and needs factors for placing and supervising offenders in the community.

Instrument description. The COMPAS is comprised of five types of scales that are overlapping: basic scales, higher order scales, validity scales, professional judgment scales, and risk scales. The basic scales tap Criminal Behavior (five scales), Needs and Social Factors (eight scales), and Personality/Cognitions, and Social Isolation (three scales). The higher order scales select items from the basic scales to tap three concepts deemed particularly relevant to reoffending: Delinquency Problems, Criminal Opportunity, and Resources/Social Capital. The validity scales are designed to assess when offenders respond defensively or carelessly to self-report survey questions. The professional judgment scales are ratings based on the evaluators' subjective judgment about the offender's risk. The risk scales are measured by outcomes of violent recidivism, failure to appear, and community noncompliance (Brennan, Fretz, & Wells, 2003). Each scale ranges from one to ten; scores from one to four are classified as low risk, scores from five to seven are classified as medium risk, and scores from eight to ten are classified as high risk.

Review of criticisms. The overwhelming majority of the research on the COMPAS comes from NorthPointe Institute for Public Management, the company that developed the measure. At the time of this study, there were only three peer-reviewed published articles on the development and psychometric properties of the instrument. Furthermore, it has not been reviewed in the *Mental Measurement Yearbook* (Carlson, Geisinger, & Spies, 2014), which provides a comprehensive guide to over 2,700 contemporary testing instruments, including information on the construction, use, validity evidence, critical reviews, and comprehensive bibliographic references of all tests.

Independent assessment of evidence by Skeem and Eno Louden (2007) raised several concerns about the COMPAS. For example, a review of validity evidence by Skeem and Eno Louden (2007) found that 15 of the 20 COMPAS scales demonstrated adequate internal consistency ($\alpha \geq .70$; Brennan, Dieterich, & Ehret, 2007; Table 2), but there was no reported data on inter-rater reliability or test-retest reliability.

Table 2.

COMPAS Scale Coefficient Alpha

Scales	*TX*	*CA 1*	*WY*	*MI*	*CA 2*	*GA*
Criminal Involvement	0.89	0.90	0.87	0.85	0.79	0.83
History of Non-Compliance	**0.56**	**0.62**	**0.68**	**0.66**	**0.57**	**0.56**
History of Violence	0.70	0.72	0.68	0.66	0.71	0.63
Current Violence	**0.67**	**0.62**	**0.64**	**0.62**	**0.67**	**0.66**
Criminal Associates/Peers	0.71	0.76	0.76	0.74	0.80	0.70
Substance Abuse	0.78	0.79	0.70	0.78	0.74	0.76
Financial Problems/Poverty	0.72	0.71	0.75	0.77	0.70	0.70
Vocational/Educational Problems	**0.69**	**0.68**	**0.65**	**0.69**	**0.67**	**0.67**
Family Criminality	**0.63**	**0.63**	**0.66**	**0.63**	**0.63**	**0.59**
Social Environment/Neighborhood	0.82	0.80	0.77	0.87	0.81	0.80
Leisure/Boredom	0.80	0.79	0.84	0.86	0.82	0.80
Residential Instability	0.63	0.68	0.69	0.68	0.71	0.65
Social Adjustment	**0.60**	**0.58**	**0.61**	**0.59**	**0.53**	**0.52**
Juvenile Socialization Problems	0.70	0.70	0.71	0.68	0.68	0.65
Criminal Opportunity	0.66	0.63	0.68	0.71	0.68	0.63
Social Isolation	0.79	0.80	0.84	0.84	0.78	0.77
Criminal Attitudes/Cognitions	0.79	0.82	0.82	0.77	0.76	0.78
Criminal Personality	0.72	0.75	0.76	0.75	0.68	0.67
Risk of Failure to Appear (FTA)	0.72	0.76	0.76	0.72	0.70	0.66
Risk of Violence	0.74	0.72	0.71	0.69	0.72	0.71

Note. TX = Dallas County Presentencing Investigations (*N* = 1,170); *CA 1* = San Bernardino, California Probations (*N* = 1,534); *WY* = Wyoming prison, parole, probation, pretrial, jail, community corrections (*N* = 1,065); *MI* = Michigan Pre-Release Assessment (*N* = 1,071); *CA 2* = Pre-Release Assessment (*N* = 1,077); *GA* = Georgia Pre-Release Assessment (*N* = 3,905).
Reproduced from Brennan, Dieterich, & Ehret (2007).

Skeem and Eno Louden (2007) also raised concerns about the construct validity of the COMPAS, including the lack of rationale with which the COMPAS items were organized to comprise the scales, and the inadequate evidence showing that the COMPAS scales correlated in the expected direction with external measures of theoretically relevant constructs. They similarly raised concerns about the predictive validity of the COMPAS, particularly the inadequate evidence linking the COMPAS scales to assessment of risk over time, response distortion, or prediction of recidivism (Skeem & Eno Louden, 2007). The problems articulated by Skeem and Eno Louden

(2007) indicated that existing studies of the COMPAS do not show adequate evidence that the COMPAS measures the contracts it purports to measure.

The available research on the COMPAS suggests its risk categories appear to predict general recidivism well, but predict violent recidivism poorly (Blomberg, Bales, Mann, Meldrum, & Nedelec, 2010). An examination of the COMPAS general recidivism risk (GRR) scale and the violent recidivism risk (VRR) scales of 91,334 parolees from the California Department of Corrections and Rehabilitation found that the predictive accuracy of parolees being re-arrested within two years of being released from prison was above chance for both risk scales. Receiver Operating Characteristic (ROC) analysis of the GRR and the VRR showed area under the curve (AUC) of .70 and .65, respectively, which led the authors to conclude that the general recidivism risk scale met the threshold for acceptability compared to leading risk assessment tools, but the violent recidivism risk scale did not meet this threshold (Farabee, Zhang, Roberts, & Yang, 2010).

Other ROC analyses of GRR and VRR using 561 inmates from Michigan Department of Corrections and 553 parolees from New York State Division of Parole found AUCs from .69 to .70, and .63 to .73, respectively (Brennan, Dieterich, Breitenbach, & Mattson, 2009). Although Brennan et al. (2009) argued that these AUC values are comparable to those found in criminal justice risk prediction studies (Brennan, Dieterich, & Ehret, 2009; Flores, Lowenkamp, Smith, & Latessa, 2006; Manchak, Skeem, & Douglas, 2008; Manchak, Skeem, Douglas, & Siranosian, 2009), those reviews were primary of the Level of Services Inventory – Revised (LSI-R; Andrews & Bonta, 1995). Skeem and Eno Louden (2007) remarked that the COMPAS performed no better than leading risk assessment and risk-needs assessment tools that have established predictive utility across sites by independent investigators.

Blomberg et al. (2010) also noted that the COMPAS risk categories for Hispanic or females who commit violence may require some adjustment. For women and Hispanics, the COMPAS risk categories of medium risk resulted in higher recidivism outcomes than those in the high-risk categories. The authors of the COMPAS conveyed that the sample sizes on which the COMPAS was validated were smaller for Hispanics and females, which reduced the reliability of the estimates. However, they did not explain why the lower sample sizes resulted in less accurate predictive validity. Independent validation study of the COMPAS recidivism score of 975 male offenders released into the community in New Jersey also found that the COMPAS recidivism score had inconsistent validity when tested on different ethnic and racial populations (Fass, Heilbrun, DeMatteo, & Fretz, 2009).

Similar to other actuarial measures, many of the items comprising the recidivism risk scale are based on static attributes of offenders. The authors of the COMPAS used four sets of variables that maximized prediction of new arrest in their algorithm for risk formulation. The first set of variables consisted of items that correlated highest with recidivism, which included age at sentencing (r = -.18), age at first arrest (r = -.28), and average arrest rate per year (r = .29). The second set of variables consisted of a newly created Drug Problems scale, which involved summing seven items, but the authors did not elaborate on the creation of the scale or the items involved in creating the scale. Notably, the original COMPAS Substance Abuse scale did not predict recidivism (r = .03), and the new Drug Problem scale was added to assist in prediction. The third set of variables includes the Professional Judgments scale, which is an average of seven COMPAS items reflecting the evaluators' ratings of the likelihood of various negative outcomes, which predicted recidivism at r = .34. Of note, the majority of the original COMPAS scales weakly predicted recidivism (r < .15). Only two (10%) of the original COMPAS scales –

Criminal Involvement (r = .20) and Vocational Educational (r = .22) – predicted recidivism strongly enough to be included in the final recidivism risk scales:

Despite the COMPAS's purported ease of use, there are a number of logistic drawbacks for using the COMPAS. The administration of the COMPAS is typically done in interview format, which often requires over 60 minutes to complete. The COMPAS items often do not ask inquire information in great detail or depth, therefore additional measures are necessary to supplement and clarify the data collected on the COMPAS. The COMPAS does not assess mental health history, therefore defendants who endorse a history of substance abuse or psychiatric treatment need an additional psychiatric interview to elaborate on the psychiatric symptoms or drug of choice. This lengthens the total administration time for each defendant, which may necessitate multiple interviews to complete the evaluation.

PAI. The Personality Assessment Inventory (PAI; Morey, 1991**,** 2007**)** is a self-report measure of adult personality and psychopathology (Morey, 1991). It consists of 344 items and 22 non-overlapping (4 validity, 11 clinical, 5 treatment, 2 interpersonal) scales that were developed based on a construct validation framework (Morey, 2003). Each item is rated on a 4-point Likert-scale (*False, Slightly True, Mostly True, Very True*) and the instrument takes between 50 to 60 minutes to complete. The instrument can be administered to individuals with a fourth grade reading level (Morey, 2001), which is lower than the reading level required for most of the other comparable self-report instruments (Morey & Quigley, 2002). This makes the PAI appropriate for the proposed study, given those forensic populations generally having lower educational levels compared to the general population.

The four validity scales (inconsistency, infrequency, negative impression, and positive impression) assess whether the respondent answered the items consistently and the response styles. The 11 clinical scales measure different areas of psychopathology, including somatic complaints, anxiety, anxiety-related disorders, depression, mania, paranoia, schizophrenia, borderline features, antisocial features, and difficulties with alcohol and drugs. The five treatment scales measures potential treatment obstacles, including aggression, suicidal ideation, stress, poor social support, and treatment rejection. The two interpersonal scales measure how the respondent relates to other people on dimensions of dominance and warmth.

The raw scores obtained on the PAI scales and subscales are transformed to T scores to provide interpretations relative to a standardization sample of 1,000 community adults. The scales are constructed such that symptom severity is reflected as an elevation on each scale. Scores above 70*T* represent a pronounced deviation from the average score of adults living in the community (Morey, 1991, 2007). Additional comparison groups have also been developed for the PAI, including scores from a clinical sample of 1,246 patients from 69 sites with different treatment settings (i.e., outpatient, inpatient, substance abuse, correctional), and scores from a correctional sample of 1,155 offenders from correctional facilities in New Jersey, Texas, Washington, and New Hampshire (Edens & Ruiz, 2005). The PAI's internal consistency, test-retest reliability, and overall validity have been well established (Morey, 1991, 2007). In addition, the PAI has proved to be a valid measure in forensic setting (Edens, Cruise, & Buffington-Vollum, 2001; Edens & Ruiz, 2005; Morey & Quigley, 2002).

VRAG. The Violence Risk Appraisal Guide (VRAG; Quinsey, Harris, Rice, & Cormier, 1998, 2006) is a purely actuarial instrument developed on a sample of 618 convicted male offenders with mental disorders in a maximum-security psychiatric hospital in Ontario, Canada. It consists of 12 static predictors identified to correlate with violent recidivism. In addition, the test developers recommend the scoring of the items be done using collateral file review rather than in conjunction with clinical judgment. The scores on the 12 items of the VRAG are then classified into nine bins or categories. Scores in bins one to three are classified as low risk, scores in bins four to six are classified as medium risk, and scores in bins seven to nine are classified as high risk.

The VRAG has been shown to yield a high degree of accuracy in the prediction of a subsequent criminal act of violence over an average time at risk of 7 years (Harris, Rice, & Camilleri, 2004). The VRAG has been shown to predict future criminal violence over follow-up periods ranging from 15 months to 10 years (Rice & Harris, 1995) and in samples with base-rates of violent recidivism ranging from 22% (Rice & Harris, 2002) to 57% (Rice & Harris, 1995). It has also been shown to predict time until the first violent re-offense and the severity of the violent offense (Harris, Rice & Cormier, 2002; Harris, Rice, Quinsey, Lalumière, Boer, & Lang, 2003). Subsequent examination of the accuracy of the VRAG risk categories two decades later found that that the instrumented predicted violent recidivism at with high levels of predictive accuracy with AUC of .75 (Rice, Harris, & Lang, 2013).

In addition to violent recidivism, the VRAG has been shown to exhibit predictive validity for general criminal recidivism (Glover, Nicholson, Hemmati, Bernfeld, & Quinsey, 2002; Gray, Fitzgerald, Taylor, MacCulloch & Snowden, 2007; Loza, Villeneuve, & Loza-Fanous, 2002; Nugent, 2001), institutional misconduct (Kroner & Mills, 2001; McBride, 1999), institutional violence (Nadeau, Nadeau, Smiley, & McHattie, 1999; Nichols, Vincent, Whittemore, & Ogloff, 1999), and sexual recidivism (Barbaree et al., 2001; Harris et al., 2003).

Treatment Noncompliance. The defendants who are accepted for jail diversion through Queens TASC Mental Health Diversion Program are under court-mandated to treatment for at least one year for felony offenses and at least 9-months for misdemeanor offenses. The court receives regular updates from TASC regarding their treatment progress. Should a violation of treatment conditions (VOC) occur, the date on which it occurs is recorded and the defendant's court case is reviewed in advance of its typical court update schedule. A defendant is considered to have violated the conditions of the treatment mandate if he or she has a new arrest, is prematurely discharged from treatment due to violating program rules, stops attending treatment, fails to appear on court dates, tests positively on multiple urine toxicology tests, or fails to adhere to other treatment mandate conditions in their pleas. For the purpose of this study, the severity of the violations is measured on an ordinal-type rating scale (1 = positive toxicology, 2 = poor compliance, 3 = program discharge, 4 = new charge). New arrests are monitored through TASC's court updates and publically accessible criminal justice database like the New York State Department of Corrections and Community Supervision Inmate Information, New York City Department of Corrections Inmate Lookup System, and the New York State Unified Court Systems WebCrims.

Procedure

The defendants were administered the PAI and the VRAG, in addition to the measures the Queens TASC Mental Health Diversion Program uses to screen for diversion eligibility and to develop treatment plans (e.g., the COMPAS). To maintain test security, the defendants who were incarcerated at the time of their evaluation were administered the PAI after they were released by the Court or on bail/bond. Archival records of defendants who were administered the PAI were also included in the analyses.

PAI data were available for all 135 defendants, but the COMPAS scores were only available for 74 defendants. The COMPAS was not included as a part of the TASC standardized screening until 2011, therefore the defendants who were referred for diversion between 2010 and

2011 did not have COMPAS data. The mechanism for which the COMPAS data were missing was related to time of the referral.

Rather than using listwise deletion to address missing data, which assumes that the remaining data are no different from missing data, multiple data were addressed with multiple imputation (Rubin, 1987, 1996) using R software (R Core Team, 2014) and Fully Conditional Specification (FCS) and Multivariate Imputation by Chained Equations (MICE) algorithm (Van Buuren & Groothuis-Oudshoorn, 1999). Multiple imputation is a method of substituting each missing value with multiple sets of plausible values using regression models. Creating different plausible versions, or multiple imputes, of the same data point simulates the variability and the uncertainty that comes with estimating missing values. The method assumes data are missing at random, meaning the reason for which the data are missing do not depend upon the values of the variable. Continuous variables were imputed using predictive mean matching (i.e., each missing value is imputed from a set of observed values that most closely match the predictor) and dichotomous variables were imputed using logistic regression. Ten imputes were created, adhering to the recommendation by Rubin (1987) that between two to ten imputations would suffice under most circumstances, depending on the fraction of missing cases. The imputed values were derived from the demographic variables from Table 1 and the PAI scales. The imputed values were pooled statistics using the MICE and semTools packages (Pornprasertmanit, Miller, Schoemann, & Rosseel, 2013) within R software.

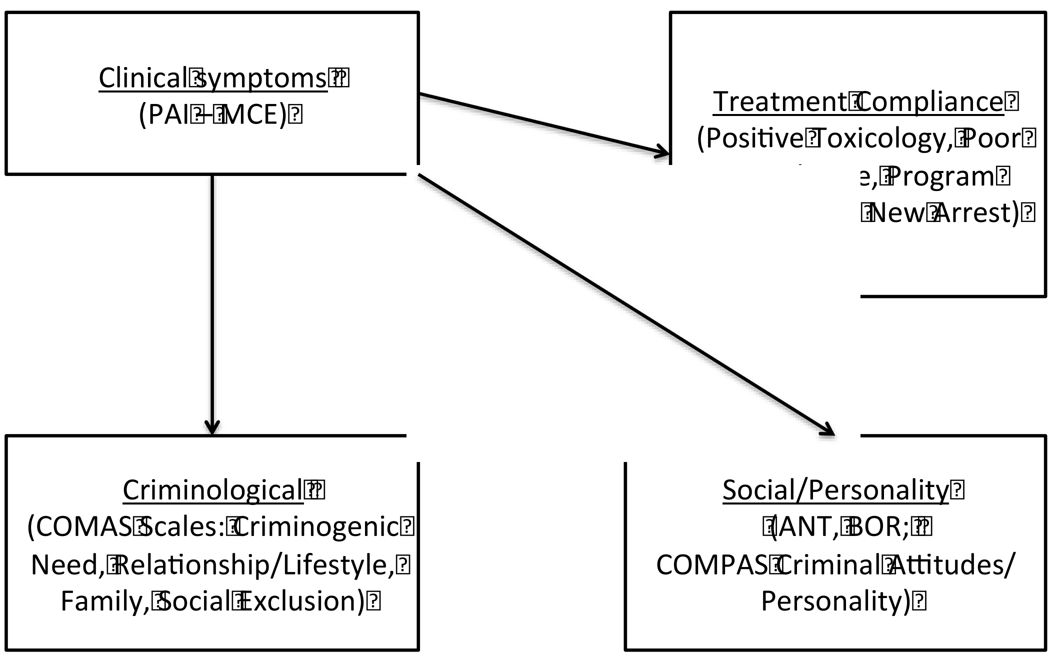
Hypotheses

Three analyses were conducted to address the respective hypotheses for this study. The first analysis examined the criminalization hypothesis. The second analysis assessed the incremental validity of measuring aggression, suicide risk, external stress, perceived lack of support, and treatment rejection for predicting diversion outcome over the recidivism risk scales measured by the COMPAS. The third analysis identified profiles that predicted treatment noncompliance.

Hypothesis 1. The first analysis examined the criminalization hypothesis that clinical symptoms fully accounted for any association between the criminological or social/personality variables with treatment noncompliance (Figure 3).

Figure 3.

Clinical Symptoms as the Sole Causal Factor of Treatment Noncompliance

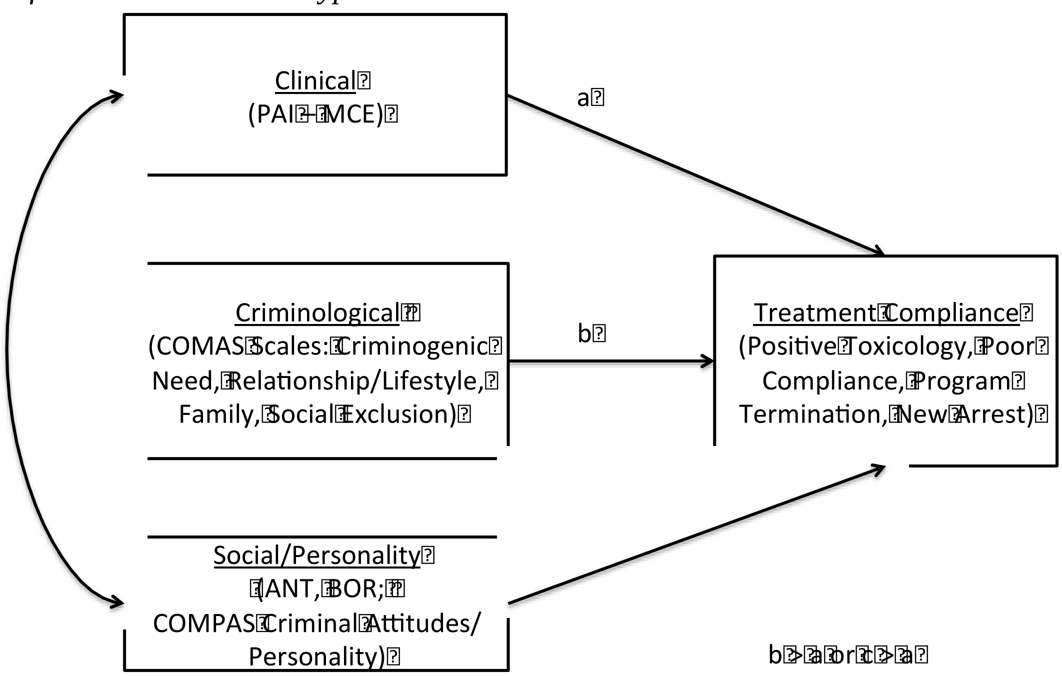


Note: PAI-MCE: Personality Assessment Inventory - Mean Clinical Elevation; ANT - Antisocial Personality Traits; BOR=Borderline Personality Traits.

This hypothesis is examined by observing the relationship between the criminological or social/personality variables with treatment noncompliance, after controlling for clinical symptoms. If the clinical symptoms account for all the variance in treatment noncompliance, then this provides partial support for the criminalization hypothesis. However, if the criminological or the social/personally variables predict treatment noncompliance, after controlling for clinical symptoms, then this does not support the criminalization hypothesis. Instead, it fails to rule out a causal role of the criminological or social/personality factors for treatment noncompliance that are not mediated by clinical symptoms. This hypothesized modification to the original criminalization hypothesis, is such that the clinical, criminological, and social/personality variables all predict treatment noncompliance, and that the criminological and social/personality factors more strongly predict treatment noncompliance (Figure 4).

Figure 4.

Modified Criminalization Hypothesis



Note: PAI-MCE: Personality Assessment Inventory Mean Clinical Elevation; ANT - Antisocial Personality Traits; BOR=Borderline Personality Traits.

Due to the sample size being insufficient for latent variable modeling, the criminalization hypothesis is examined using Cox proportional-hazards regression models for observed variables (Cox, 1972). The hazard is time to treatment noncompliance. The clinical factor is measured by the mean elevation of the PAI clinical scales (MCE). The criminological factor is measured by the COMPAS Criminogenic Need, COMPAS Relationship/Lifestyle, COMPAS Family, and the

COMPAS Social Exclusion scales. The Social/Personality factor is measured by the PAI Borderline Features (*BOR*), PAI Antisocial Features (*ANT*), and the COMPAS personality/attitudes scales. Treatment noncompliance is measured by days to violation of treatment conditions (VOC) report.

Hypothesis 2. The second analysis assessed the incremental validity of the PAI treatment scales and the VRAG over the COMPAS General Recidivism Risk (GRR) and the COMPAS Violent Recidivism Risk (VRR) scales for predicting diversion outcome. The PAI treatment scales measure a number of constructs that are associated with treatment outcome, including aggression, suicide risk, external stressors, perceived lack of support, and treatment rejection. The hypothesis that PAI treatment scales or the VRAG predicts treatment noncompliance above and beyond the criminological factors measured by the COMPAS is demonstrated by an improvement in model fit to the Cox regression model after entering the PAI treatment scales to the COMPAS GRR and VRR. The analysis was repeated, adding the VRAG to the COMPAS GRR and VRR to examine whether it added incremental validity to the COMPAS.

Hypothesis 3. The third analysis identified PAI profiles that predict various types of treatment noncompliance. Bivariate correlations examine the association between the PAI scales with different forms of treatment noncompliance. Profiles were created by examining the improvement in model fit after entering individual PAI scales to the Cox regression model to predict different types of noncompliance. Although hospitalizations are not considered violations of treatment condition by the mental health court, it is operationalized as a negative outcome in this analysis from a cost-benefit analysis perspective because they utilize additional financial resources and is contrary to the purpose of diverting individuals with mental illness to community mental health treatment. The created profiles were then entered as predictors in a Poisson regression model to predict the frequency of treatment violations and in a linear regression model to predict the severity of treatment violations.

Power Analysis. A cox regression model is equivalent to a Poisson regression that counts the observation times until a violation occurs. Power analysis, using G*Power v3.1 (Erdfelder, Faul, & Buchner, 1996), shows that a Poisson regression model with a sample size of 125, 0.80 power, 0.05 alpha, can detect a change in the rate of violations of 10% given an increase in predictor score of 1/2 *SD*.

CHAPTER III

Results

Among the total sample of 135 defendants who were referred for diversion, Queens TASC Mental Health Diversion Program accepted 98 defendants for diversion. Of the 98 defendants accepted by Queens TASC Mental Health Diversion Program, 14 PAI profiles were invalid due to excessive number of omitted items (i.e., greater than 18) or inconsistent responding, as measured by inconsistency (*ICN*) or infrequency (*INF*) scales (Table 3). The proportion of invalid PAI profiles due to inconsistent responding was similar between the total sample of defendants who were referred for diversion and the defendants who were accepted by Queens TASC Mental Health Diversion Program for diversion, $\chi^2(1, N=135) = .03$, $p = .86$. A final sample of 84 defendants was included in all analyses.

Table 3.

Rates of Invalid PAI Protocols

	Total (*N* = 135)		**Accepted (*n* = 98)**		**Rejected (*n* = 37)**	
	Freq	**%**	***Freq***	**%**	***Freq***	**%**
Invalid (Total)	18	13.3	14	14.3	4	10.8
ICN ≥ 73*T*	8	5.9	7	7.1	1	2.7
INF ≥ 75*T*	13	9.6	9	9.2	4	10.8
Missing ≥ 18	1	0.7	0	0.0	1	2.7
ICN ≥ 73*T* & *INF* ≥ 75*T*	3	2.2	2	2.3	1	2.7
Valid	117	86.7	84	85.7	33	89.2

Note. *ICN* = Inconsistency; *INF* = Infrequency.

Of the 84 defendants who were accepted for jail diversion, approximately half of the defendants did not have any major compliance-related issues (Table 4). Approximately one-third of the defendants who completed the treatment mandate successfully had one court update related to poor compliance and about 17% of the defendants repeatedly had difficulties related to compliance. Not surprisingly, the defendants who failed court mandated treatment had more frequent problems with treatment noncompliance than the defendants who completed court mandate treatment, $t(72) = 4.10$, $p < .001$. In addition, the defendants who failed court mandated treatment had more severe treatment violations than the defendants who completed court mandated treatment, $t(11.20) = 3.10$, $p = .01$.

Table 4.

Compliance by Treatment Outcome

	Total (N = 84)		Completed (n = 51)		Failed (n = 11)		Pending (n = 22)	
	Freq	***%***	***Freq***	***%***	***Freq***	***%***	***Freq***	***%***
Violation of								
0	41	48.8	31	60.8	1	9.1	9	40.9
1	27	32.1	15	29.4	4	36.4	8	36.4
2 or more	16	19.0	5	9.8	6	54.5	5	20.8
Remanded	27	32.1	8	15.7	11	100.0	8	36.4
New Charge	17	20.2	8	15.7	5	45.4	4	18.2
Hospitalized	11	13.1	4	7.8	3	27.3	4	18.2
	M	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Severity	1.94	2.65	1.14	1.76	5.09	3.33	2.73	3.54

Descriptive statistics of the defendants' COMPAS, PAI, and VRAG scores show that the COMPAS and the VRAG contained missing data (Table 5). Ten imputed values were created for each missing value to more accurately estimate the variability of missing data. The mean and standard deviation of the pooled imputed data for the COMPAS and the VRAG appear similar to the observed data. The largest difference in mean (.37) and standard deviation (.09) was for the COMPAS family scale.

Table 5.

Distribution of the Observed and Imputed Scores

	Observed Data				Imputed Data		
Scales	*M*	*SD*	Range	*N*	*M*	*SD*	Range
PAI MCE T	60.17	9.88	41 – 86	84	60.34	9.72	41 – 86
PAI *BOR* T	62.64	13.79	40 – 97	84	62.91	13.89	34 – 97
PAI *ANT* T	58.58	12.26	37 – 95	84	58.23	11.84	37 – 95
PAI *ALC* T	57.57	16.44	41 – 104	84	57.18	15.68	41 – 104
PAI *DRG* T	67.93	17.95	42 – 112	84	67.49	17.14	42 – 112
PAI *AGG* T	53.64	13.18	35 – 88	84	54.43	13.36	32 – 88
PAI *SUI* T	55.60	12.30	43 – 95	84	56.34	12.57	43 – 105
PAI *STR* T	63.86	10.93	41 – 86	84	64.06	11.64	37 – 91
PAI *NON* T	56.39	13.55	37 – 99	84	57.62	14.04	37 – 99
PAI *RXR* T	42.54	11.72	20 – 68	84	42.71	11.84	20 – 72
COMPAS GRR	2.91	2.32	1 – 10	57	3.10	2.27	1 – 10
COMPAS VRR	3.02	2.28	1 – 9	57	3.19	2.32	1 – 10
COMPAS Criminogenic	2.84	1.78	1.00 – 7.33	57	3.02	1.82	1.00 – 8.33
COMPAS Lifestyle	5.48	1.91	1.50 – 9.50	57	5.37	1.86	1.25 – 9.75
COMPAS Personality	5.92	2.27	1.00 – 9.67	57	5.88	2.20	1.00 – 9.67
COMPAS Family	3.03	2.14	1.00 – 8.50	57	3.48	2.32	1.00 – 10.00
COMPAS Exclusion	5.00	1.92	1.00 – 9.40	57	4.90	1.84	1.00 – 9.40
VRAG Risk Category	4.86	1.37	2.00 – 8.00	65	4.96	1.42	2 - 8

Note. PAI = Personality Assessment Inventory; MCE = Mean clinical elevation; *BOR* = Borderline Features; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression; *SUI* = Suicide Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection; GRR = General Recidivism Risk; VRR = Violence Recidivism Risk; VRAG = Violence Risk Appraisal Guide.

Descriptive statistics of the valid PAI profiles show that with the exception of the Warmth (*WRM*) scale, the Queens TASC Mental Health Diversion Program sample had elevations on all scales that were statistically significantly higher than the standardization sample (Table 6). For ease of comparison, the clinical and the correctional comparison groups were transformed into T scores relative to the standardized sample. Figure 5 shows that PAI scale elevations appear to more closely approximate the clinical sample than the community standardization sample or the correctional sample. This suggests that the clinical normative sample may be an appropriate comparison group for measuring psychopathology for the defendants referred for jail diversion.

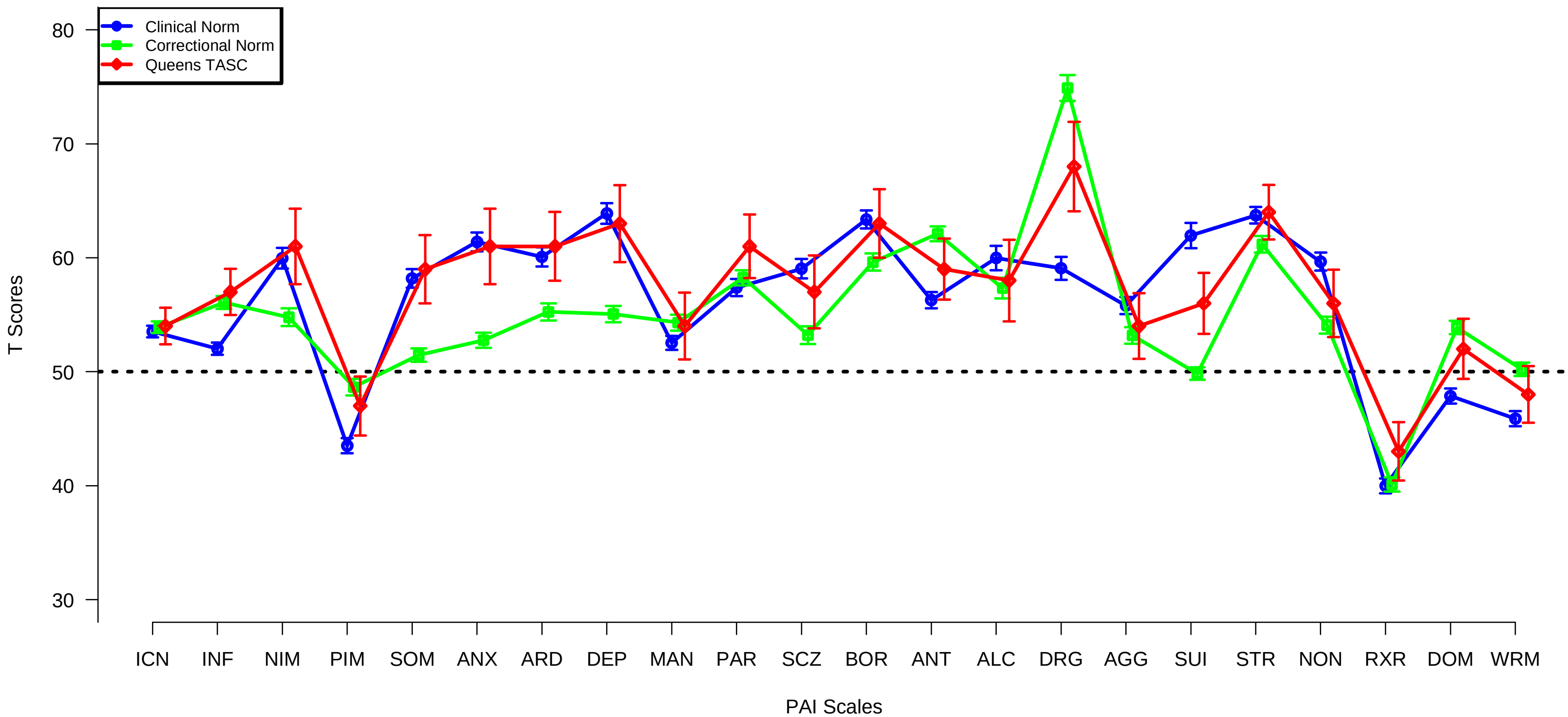
Table 6.

Comparison of Queens TASC PAI Scores to Normative Samples

Scale	*M*	*SD*	Standardized T Score	d^a	Clinical T Score	d^b	Correctional T Score	d^c
ICN	6.80	2.44	54	.43*	51	.08	50	.03
INF	4.35	2.39	57	.66*	55	.47*	50	.05
NIM	4.75	4.12	61	1.08*	51	.09	55	.49*
PIM	13.83	5.19	47	-.28*	53	.31*	49	-.12
SOM	19.98	13.85	59	.85*	50	.04	57	.71*
ANX	28.29	16.02	61	1.07*	50	-.01	57	.73*
ARD	28.98	11.52	61	1.06*	51	.06	54	.23*
DEP	26.18	14.56	63	1.20*	49	-.08	56	.61*
MAN	26.31	12.36	54	.34*	51	.09	49	-.06
PAR	28.29	11.11	61	1.11*	53	.30*	53	.27*
SCZ	19.13	11.31	57	.63*	48	-.16	52	.25*
BOR	30.70	13.82	63	1.23*	50	-.05	52	.24*
ANT	21.04	11.16	59	.85*	52	.19	47	-.31*
ALC	9.08	9.19	58	.71*	49	-.13	50	.02
DRG	12.96	8.97	68	1.64*	55	.49*	46	-.37*
AGG	17.89	11.12	54	.36*	48	-.16	50	.04
SUI	6.15	5.93	56	.58*	47	-.32*	56	.64*
STR	11.83	4.96	64	1.34*	50	-.01	52	.19
NON	7.33	5.08	56	.64*	48	-.22	52	.20
RXR	10.23	5.45	43	-.75*	52	.21	52	.22
DOM	21.33	6.75	52	.13	53	.30*	48	-.25*
WRM	22.24	6.40	48	-.22	52	-.16	48	-.25*
Supplemental								
DEF	2.49	2.05	47	-.35*	55	.46*	–	–
CDF	141.03	20.82	52	.19	53	.30*	–	–
MAL	.73	.92	54	.25*	49	-.07	–	–
RDF	-.68	1.17	53	.29*	54	.40*	–	–
SPI	7.81	5.02	65	1.37*	50	-.01	–	–
VPI	4.87	4.02	64	1.39*	41	.12	–	–
TPI	0.82	1.26	65	-0.16	41	-.97*	–	–

Note. *d* = Cohen's d; *ICN* = Inconsistency; *INF* = Infrequency; *NIM* = Negative Impression Management; *PIM* = Positive Impression Management; *SOM* = Somatic Complaints; *ANX* = Anxiety; *ARD* = Anxiety-Related Disorder; *DEP* = Depression; *MAN* = Mania; *PAR* = Paranoia; *SCZ* = Schizophrenia; *BOR* = Borderline Features; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression; *SUI* = Suicide Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection; *DOM* = Dominance; *WRM* = Warmth; *DEF* = Defensive Index; *CDF* = Cashel Discriminant Function; *MAL* = Malingering Index; *RDF* = Rogers Discriminant Function; *SPI* = Suicide Potential Index; *VPI* = Violence Potential Index; *TPI* = Treatment Potential Index.
[a]Compared to Standardization Sample (*N* = 1,000); [b]Compared to Clinical Sample (*N* = 1,246); [c]Compared to Correctional Sample (*N* = 1,155). The supplemental scales are not calculated in the corrections normative sample.
*$p < .05$.

Figure 5. *Comparison of TASC PAI Scales with Clinical and Corrections Normative Samples*



Note. ICN = Inconsistency; *INF* = Infrequency; *NIM* = Negative Impression Management; *PIM* = Positive Impression Management; *SOM* = Somatic Complaints; *ANX* = Anxiety; *ARD* = Anxiety-Related Disorder; *DEP* = Depression; *MAN* = Mania; *PAR* = Paranoia; *SCZ* = Schizophrenia; *BOR* = Borderline Features; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression; *SUI* = Suicide Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection; *DOM* = Dominance; *WRM* = Warmth.

Coefficient α show good internal consistency for all PAI scales and subscales. The majority of the scales demonstrate $\alpha \geq .80$, with the lowest α at .68 (Table 7). Because coefficient α can elevate as a result of high item correlations, regardless of dimensionality, coefficient omega[1] (ω; McDonald, 1999) was calculated to aid the estimation of internal consistency and unidimensionality. Omega_hiearchical (ω_h) was used to estimate the internal consistency of scales comprised of subscales, whereas Omega_total (ω_t) was used to estimate scale reliabilities of individual scales and subscales. Coefficient omega shows that the individual scales and subscales generally have reliable variance, but the scales comprised of subscales do not have reliable variance that is shared across the subscales. For example, the SCZ scale has α of .88 but ω_h of .46, but ω_t of each subscale comprising the SCZ are over .78. This indicates that SCZ has reliable variance, but it is not shared across all the items across the subscales.

Table 7.

Internal Consistency Estimates of PAI Scales

Scale	α	ω	Mean interitem Correlation
Negative Impression Management (*NIM*)	.67	.68	.19
Positive Impression Management (*PIM*)	.76	.77	.26
Somatic Complaints (*SOM*)	.91	**.68**[a]	.29
Conversion (*SOM-C*)	.81	.81	.35
Somatization (*SOM-S*)	.70	.73	.22
Health Concerns (*SOM-H*)	.82	.83	.35
Anxiety (*ANX*)	.94	**.68**[a]	.39
Cognitive (*ANX-C*)	.86	.86	.43
Affective (*ANX-A*)	.79	.80	.31
Physiological (*ANX-P*)	.86	.86	.43
Anxiety-Related Disorders (*ARD*)	.82	**.51**[a]	.17
Obsessive-Compulsive (*ARD-O*)	.59	.61	.15
Phobias (*ARD-P*)	.64	.65	.18
Traumatic Stress (*ARD-T*)	.87	.88	.45
Depression (*DEP*)	.92	.74[a]	.33

[1] ω_h was found to be the best estimate of scale reliabilities when compared to Cronbach's α and Revelle's β (Zinbarg, Revelle, Yovel, & Li, 2005).

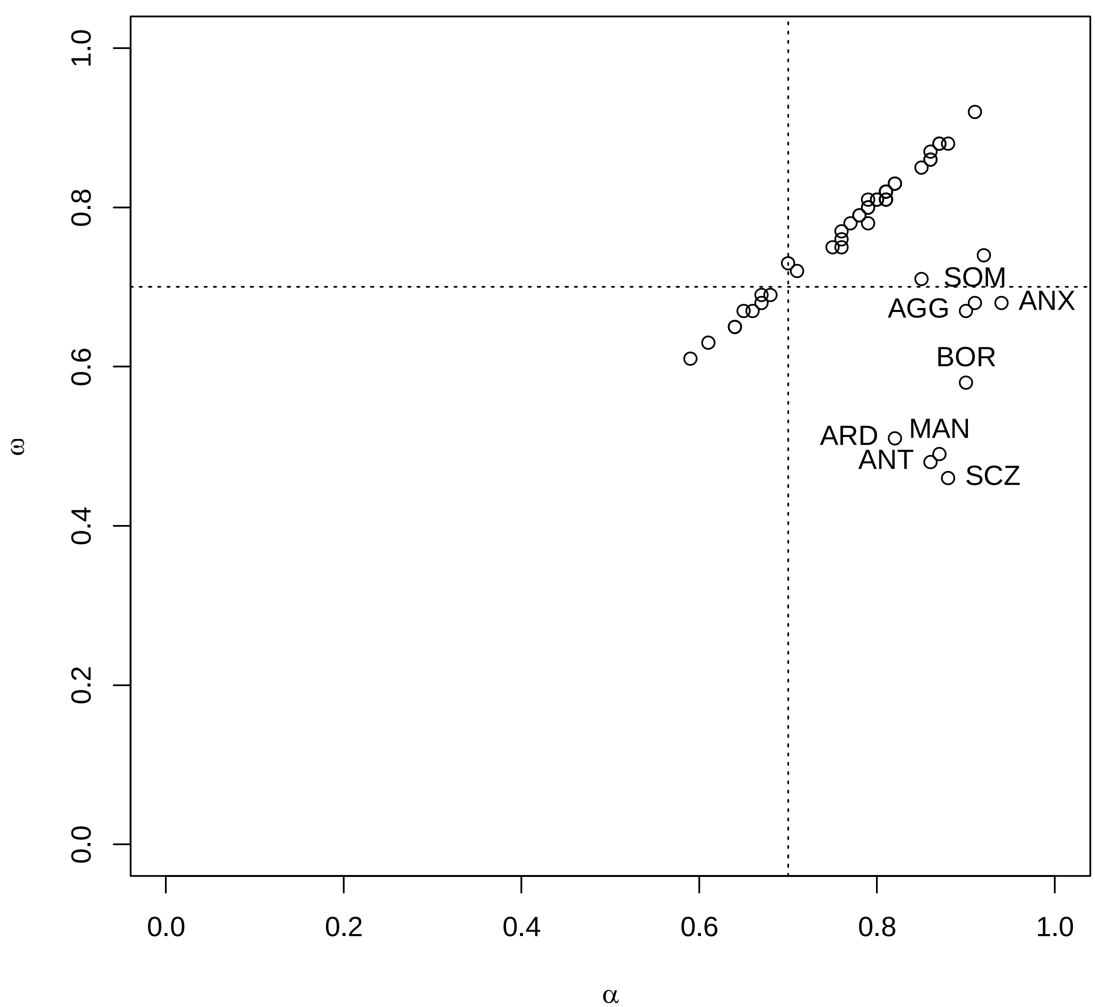
Cognitive (*DEP-C*)	.80	.81	.33
Affective (*DEP-A*)	.88	.88	.47
Physiological (*DEP-P*)	.77	.78	.30
Mania (*MAN*)	.87	**.49**[a]	.22
Activity Level (MAN-A)	.61	.63	.17
Grandiosity (MAN-G)	.81	.82	.35
Irritability (MAN-I)	.85	.85	.41
Paranoia (*PAR*)	.85	.71[a]	.19
Hypervigilance (*PAR-H*)	.67	.69	.20
Persecution (*PAR-P*)	.79	.81	.31
Resentment (*PAR-R*)	.65	.67	.19
Schizophrenia (*SCZ*)	.88	**.46**[a]	.23
Psychotic Experiences (*SCZ-P*)	.79	.78	.32
Social Detachment (*SCZ-S*)	.81	.81	.34
Thought Disorder (*SCZ-T*)	.82	.83	.37
Borderline Features (*BOR*)	.90	**.58**[a]	.27
Affective Instability (*BOR-A*)	.81	.81	.42
Identity Problems (*BOR-I*)	.76	.76	.35
Negative Relationships (*BOR-N*)	.64	.65	.23
Self-Harm (*BOR-S*)	.78	.79	.38
Antisocial Features (*ANT*)	.86	**.48**[a]	.21
Antisocial Behaviors (*ANT-A*)	.75	.75	.27
Egocentricity (*ANT-E*)	.66	.67	.19
Stimulus-Seeking (*ANT-S*)	.76	.75	.28
Alcohol Problems (*ALC*)	.91	.92	.46
Drug Problems (*DRG*)	.87	.88	.36
Aggression (*AGG*)	.90	**.67**[a]	.33
Aggressive Attitude (AGG-A)	.81	.82	.42
Verbal Aggression (AGG-V)	.71	.72	.29
Physical Aggression (AGG-P)	.79	.80	.39
Suicidal Ideation (*SUI*)	.86	.87	.34
Stress (*STR*)	.68	.69	.21
Nonsupport (*NON*)	.80	.81	.34
Treatment Rejection (*RXR*)	.81	.82	.34
Dominance (*DOM*)	.81	.82	.27
Warmth (*WRM*)	.78	.79	.23

Note. α = Coefficient alpha, ω_t = Coefficient Omega_total.
Reliability estimates were not calculated for *ICN* and *INF* scales because these scales were not designed to assess internally consistent constructs.
[a]Coefficient Omega_hierarchical estimations were used for scales comprised of subscales.

Figure 6 shows a scatterplot of coefficient *α* on the x-axis and coefficient *ω* on the y-axis. The dotted lines, representing the internal scale consistency of .70, split the plot into four quadrants. The scales with both acceptable coefficient alpha and coefficient omega fall in the top right quadrant. Six scales have acceptable coefficient α but low coefficient ω and are labeled in the plot.

This is consistent with the construct validation framework from which the PAI was created, namely to reflect the heterogeneity and multidimensional underlying the construct of clinical syndromes (Morey, 1991; 2007). This also supports the interpretation of the PAI at the subscale level, because the constructs underlying the primary scales are not simply sum of its subscales.

Figure 6. *Coefficient Alpha by Coefficient Omega*



Note. *SOM* = Somatic Complaints; *ANX* = Anxiety; *ARD* = Anxiety-Related Disorder; *SCZ* = Schizophrenia; *BOR* = Borderline Features; *ANT* = Antisocial Features; *AGG* = Aggression.

Analysis 1

The first analysis examined the criminalization hypothesis that clinical symptoms fully account for any association between the criminological factors or social/personality factors with treatment compliance. If the criminological (COMPAS criminogenic need, COMPAS relationship/lifestyle, COMPAS family, and COMPAS Social Exclusion scales) or the social/personality variables (PAI borderline personality features, PAI antisocial personality features, and the COMPAS personality/attitudes scales) continue to predict treatment noncompliance after controlling for clinical symptoms (MCE), then it does not support the strict interpretation of the criminalization hypothesis. Instead, it fails to rule out a causal role for criminological and social/personality factors that are not mediated by clinical factors. If either the criminological or the social/personality factor drops below statistical significance, then this partially supports the criminalization hypothesis.

The Cox proportional-hazards regression model, predicting treatment noncompliance from the clinical and criminological variables, shows that neither clinical factors nor criminological factors predict treatment noncompliance (Table 8; Table 9).

Table 8.

Chi-square Values for Cox Regression Model Predicting Noncompliance Using Clinical and Criminological Factors

	χ^2 Model			χ^2 Difference		
Model	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Noncompliance ~ Clinical + Criminological	6.76	5	.24	–	–	–
Noncompliance ~ Clinical	1.45	1	.23	5.31	4	.26

Note. N = 84.
Analysis with pooled imputed data.

Table 9.

Cox Regression Estimates Predicting Noncompliance Using Clinical and Criminological Factors

	B (SE)	HR	*LL*	*UL*	*p*
Model 1: Noncompliance ~ Clinical					
MCE (Clinical)	.02 (.02)	1.02	.99	1.05	.23
Model 2: Noncompliance ~ Clinical + Criminological					
MCE (Clinical)	.01 (.02)	1.01	.98	1.04	.67
Criminogenic Need (Criminological)	.01 (.12)	1.01	.79	1.29	.92
Lifestyle (Criminological)	.19 (.12)	1.21	.97	1.52	.09
Family (Criminological)	.01 (.08)	1.01	.86	1.19	.88
Social Exclusion (Criminological)	.04 (.12)	1.04	.83	1.32	.72

Note. *N* = 84. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; MCE = Mean clinical elevation. Analysis with pooled imputed data. Appendix B shows results after listwise deletion for comparison.

Cox proportional-hazards regression model, predicting treatment noncompliance from clinical and social/personality factors shows that the social/personality variables added incremental predictive validity to treatment noncompliance (Table 10). Within the social/personality factor, the PAI ANT scale was the only statistically significant predictor, indicating an increase of one T score on ANT increased the hazard of treatment noncompliance by a factor of 1.03, or 3% (Table 11). This indicates that having personality traits related to difficulties with authority and following rules, irresponsible, egocentric, reckless, and impulsive, increased risk of treatment noncompliance.

Table 10.

Chi-square Values for Cox Regression Model Predicting Noncompliance using Clinical and Social/Personality Factors

	χ^2 Model			χ^2 Difference		
Model	χ^2_M	df_M	*p*	$\Delta\chi^2$	Δdf	*p*
Noncompliance ~ Clinical + Social/Personality	9.77	4	**.04**	–	–	–
Noncompliance ~ Clinical	1.45	1	.23	8.32	3	**.04**

Note. *N* = 84.
Analysis with pooled imputed data.

Table 11.

Cox Regression Estimates Predicting Noncompliance Using Clinical and Social/Personality Factors

	B (SE)	HR	*LL*	*UL*	*p*
Model 1: Noncompliance ~ Clinical					
MCE (Clinical)	.02 (.02)	1.02	.99	1.05	.23
Model 2: Noncompliance ~ Clinical + Social/Personality					
MCE (Clinical)	.01 (.03)	1.01	.96	1.06	.82
BOR (Social/Personality)	-.01 (.02)	.99	.95	1.03	.73
ANT (Social/Personality)	.03 (.01)	1.03	1.00	1.06	**.03**
Personality (Social/Personality)	.04 (.10)	1.05	.85	1.28	.67

Note. *N* = 84. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; MCE = Mean Clinical Elevation; *BOR* = Borderline Personality Traits; *ANT* = Antisocial Personality Traits.
Analysis with pooled imputed data. Appendix C shows results after listwise deletion for comparison.

The clinical symptoms did not predict treatment noncompliance at a statistically significant level. In fact, only the social/personality variable, specifically antisocial personality features, was a statistically significant predictor of treatment noncompliance. These findings do not support the strict interpretation of the criminalization explanation that untreated clinical symptoms affects recidivism. Instead, the analyses provide partial support that social/personality variables not only affect treatment noncompliance, but also have larger effects than both clinical and criminological variables for predicting treatment noncompliance.

Analysis 2

The second analysis examined the incremental validity of the PAI treatment scales and the VRAG over the COMPAS GRR and VRR scales for predicting diversion outcome. The hypothesis that PAI treatment scales or the VRAG can predict outcome above and beyond the COMPAS is demonstrated by improvement in model fit after adding the PAI treatment scales to the COMPAS recidivism scales.

Cox proportional-hazards regression model, predicting diversion outcome from GRR and VRR shows that the COMPAS recidivism scales did not predict diversion outcome at a statistically significant level (Table 12; Table 13). The addition of the PAI treatment scales did not improve at a statistically significant level or add incremental validity to the COMPAS.

Table 12.

Chi-square Values for Cox Regression Predicting Mandate Status Using the COMPAS and the PAI

	χ^2_{Model}			$\chi^2_{\text{Difference}}$		
Model	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Mandate Status ~ COMPAS + PAI Treatment Scales	5.19	7	.64	–	–	–
Mandate Status ~ COMPAS	.35	2	.84	4.84	5	.43

Note. $N = 84$.
Analysis with pooled imputed data.

Table 13.

Cox Regression Estimates Predicting Mandate Status Using the COMPAS and the PAI

	B (SE)	HR	*LL*	*UL*	*p*
Model 1: Mandate Status ~ COMPAS					
GRR (COMPAS)	-.11 (.32)	.90	.48	1.69	.73
VRR (COMPAS)	.15 (.27)	1.16	.68	2.00	.57
Model 2: Mandate Status ~ COMPAS + PAI Treatment Scales					
GRR (COMPAS)	-.14 (.40)	.87	.39	1.97	.73
VRR (COMPAS)	.28 (.36)	1.32	.64	2.76	.44
AGG (PAI)	.03 (.04)	1.03	.96	1.11	.37
SUI (PAI)	.04 (.04)	1.04	.96	1.12	.37
STR (PAI)	-.05 (.06)	.95	.85	1.07	.39
NON (PAI)	.05 (.06)	1.05	.93	1.18	.42
RXR (PAI)	.05 (.06)	1.05	.94	1.17	.42

Note. *N* = 84. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; GRR = General Recidivism Risk; VRR = Violent Recidivism Risk; *AGG* = Aggression; *SUI* = Suicidal Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection.
Analysis with pooled imputed data.

Cox proportional-hazards regression model, predicting diversion outcome using the COMPAS recidivism scales and the VRAG also did not yield statistical significance (Table 14; Table 15). The addition of the VRAG did not improve at a statistically significant level or add incremental validity to the COMPAS.

Table 14.

Chi-square Values for Cox Regression Predicting Mandate Status Using the COMPAS and the VRAG

	χ^2 Model			χ^2 Difference		
Model	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Mandate Status ~ COMPAS + VRAG	.01	3	.99	–	–	–
Mandate Status ~ COMPAS	.35	2	.84	.34	1	.56

Note. *N* = 84.
Analysis with pooled imputed data.

Table 15.

Cox Regression Predicting Mandate Status Using the COMPAS and the VRAG

	B (SE)	HR	*LL*	*UL*	*p*
Model 1: Mandate Status ~ COMPAS					
GRR (COMPAS)	-.11 (.32)	.90	.48	1.69	.73
VRR (COMPAS)	.15 (.27)	1.16	.68	2.00	.57
Model 2: Mandate Status ~ COMPAS + VRAG					
GRR (COMPAS)	-.12 (.35)	.89	.44	1.79	.73
VRR (COMPAS)	.16 (.29)	1.18	.66	2.09	.57
VRAG	.24 (.33)	1.27	.66	2.43	.47

Note. *N* = 84. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; GRR = General Recidivism Risk; VRR = Violent Recidivism Risk; VRAG = Violence Risk Appraisal Guide Risk Category.
Analysis with pooled imputed data.

These results suggest that neither the COMPAS recidivism scales, the PAI treatment scales nor the VRAG predicted diversion outcome at a level that could be detected with the current sample size. Power analysis show that with a change in predictor of about one T score or 0.1 *SD*, a sample size of over 800 would be necessary in order to achieve statistical significance at the .05 alpha level.

Examination of the PAI profile by the status of treatment mandate completion shows that they have similar scale elevations (Table 16; Figure 7; Figure 8).

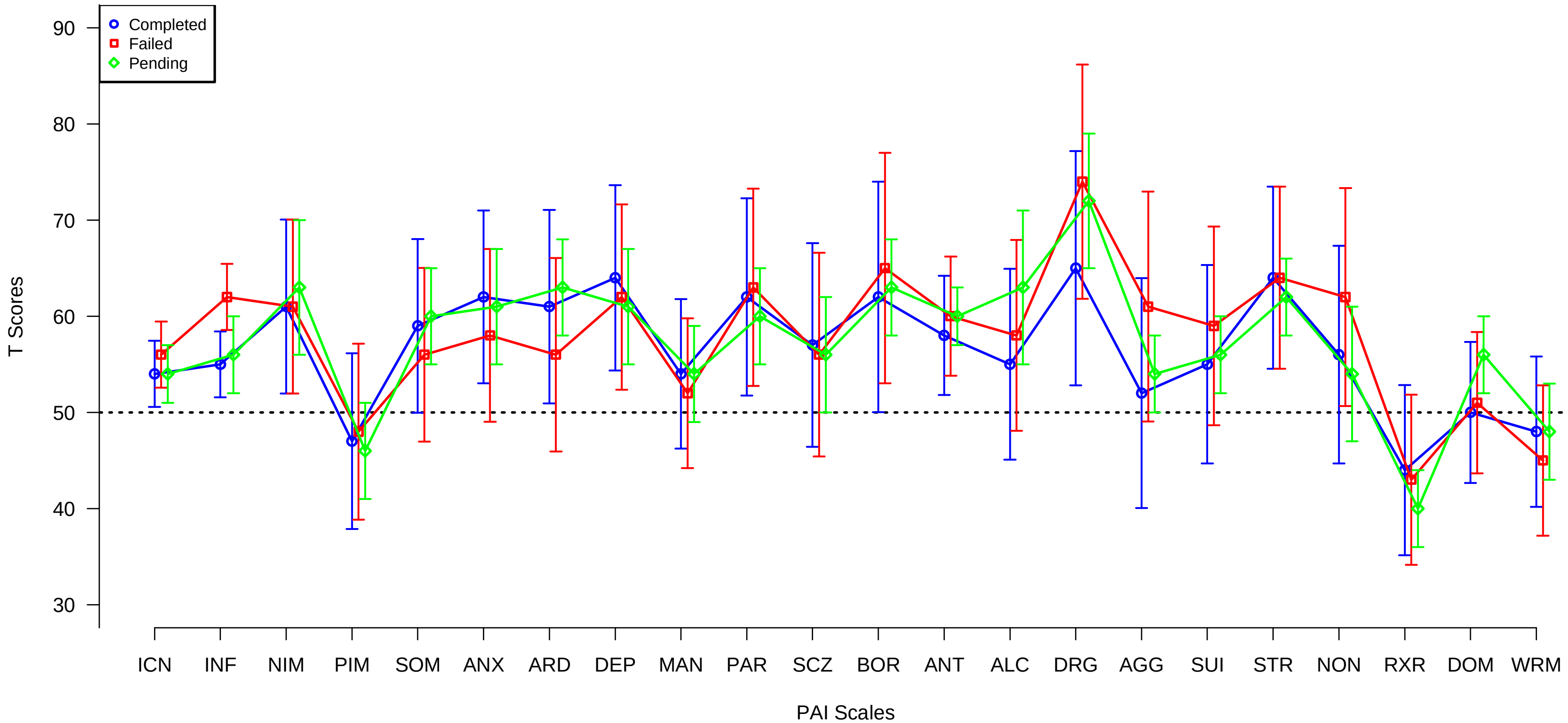
Table 16.

PAI Scales by Mandate Status

	Completed (*n* = 51)			Failed (*n* = 11)			Pending (*n* = 22)		
Scale	*M*	*SD*	*T*	*M*	*SD*	*T*	*M*	*SD*	*T*
ICN	6.78	2.54	54	7.27	1.90	56	6.59	2.52	54
INF	4.06	2.40	55	5.73	1.42	62	4.32	2.57	56
NIM	4.55	4.13	61	4.64	4.08	61	5.27	4.26	63
PIM	13.96	5.12	47	14.27	6.57	48	13.32	4.78	46
SOM	20.18	14.71	59	16.82	14.98	56	21.09	11.39	60
ANX	29.08	16.43	62	24.55	15.81	58	28.32	15.60	61
ARD	28.98	11.72	61	25.18	13.80	56	30.86	9.77	63
DEP	27.12	15.22	64	25.55	15.06	62	24.32	13.12	61
MAN	26.43	13.03	54	24.55	11.81	52	26.91	11.43	54
PAR	28.53	10.35	62	29.45	14.73	63	27.14	11.28	60
SCZ	19.59	11.06	57	18.45	13.55	56	18.41	11.22	56
BOR	30.33	13.28	62	32.73	19.89	65	30.55	12.01	63
ANT	20.25	12.93	58	22.64	9.32	60	22.05	7.03	60
ALC	7.73	8.49	55	9.18	9.26	58	12.18	10.34	63
DRG	11.39	8.84	65	16.09	10.09	74	15.05	8.25	72
AGG	16.22	10.23	52	24.55	16.77	61	18.45	8.66	54
SUI	5.73	5.89	55	7.64	8.27	59	6.41	4.72	56
STR	12.00	4.89	64	12.09	6.98	64	11.32	4.09	62
NON	7.31	4.27	56	9.45	6.95	62	6.32	5.65	54
RXR	10.71	5.53	44	10.36	6.80	43	9.05	4.54	40
DOM	20.22	6.92	50	21.18	6.85	51	24.00	5.77	56
WRM	22.41	6.16	48	20.73	7.35	45	22.59	6.67	48
DEF	2.57	2.17	48	2.45	2.25	47	2.32	1.70	46
CDF	142.29	19.04	53	143.93	29.30	54	136.66	20.33	49
MAL	.69	.91	53	.55	.69	51	.91	1.06	56
RDF	-.69	1.13	53	-.67	.92	53	-.65	1.38	53
SPI	7.80	4.75	65	8.00	7.21	65	7.73	4.60	64
VPI	4.69	3.96	63	5.91	5.54	69	4.77	3.35	64
TPI	.92	1.28	64	1.27	1.74	66	.36	.79	67

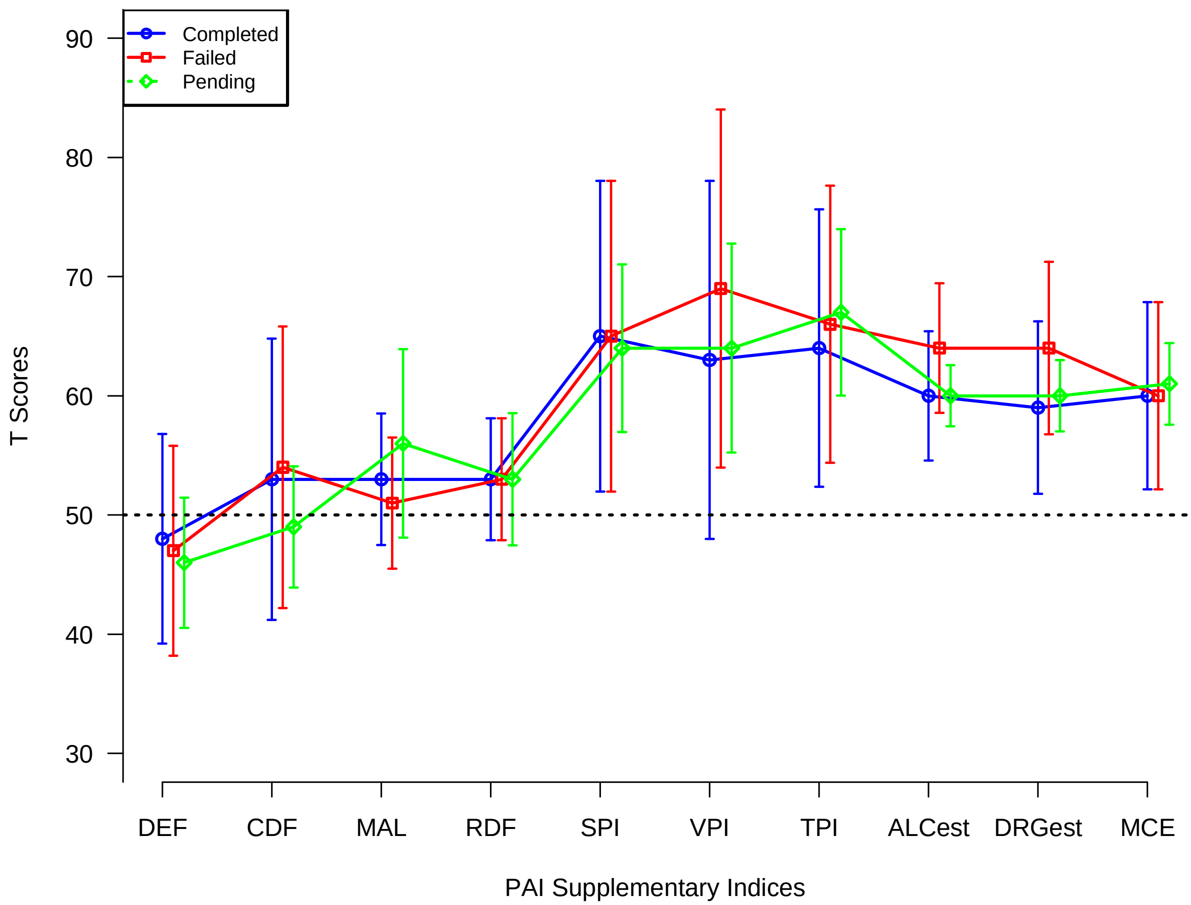
Note. *ICN* = Inconsistency; *INF* = Infrequency; *NIM* = Negative Impression Management; *PIM* = Positive Impression Management; *SOM* = Somatic Complaints; *ANX* = Anxiety; *ARD* = Anxiety-Related Disorder; *DEP* = Depression; *MAN* = Mania; *PAR* = Paranoia; *SCZ* = Schizophrenia; *BOR* = Borderline Features; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression; *SUI* = Suicide Ideation; STR = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection; *DOM* = Dominance; *WRM* = Warmth; *DEF* = Defensive Index; *CDF* = Cashel Discriminant Function; *MAL* = Malingering Index; *RDF* = Rogers Discriminant Function; *SPI* = Suicide Potential Index; *VPI* = Violence Potential Index; *TPI* = Treatment Potential Index.

Figure 7. *PAI Scales by Mandate Status*



Note. *ICN* = Inconsistency; *INF* = Infrequency; *NIM* = Negative Impression Management; *PIM* = Positive Impression Management; *SOM* = Somatic Complaints; *ANX* = Anxiety; *ARD* = Anxiety-Related Disorder; *DEP* = Depression; *MAN* = Mania; *PAR* = Paranoia; *SCZ* = Schizophrenia; *BOR* = Borderline Features; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression; *SUI* = Suicide Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection; *DOM* = Dominance; *WRM* = Warmth.

Figure 8. *PAI Supplemental Indices by Mandate Status*



Note. *DEF* = Defensive Index; *CDF* = Cashel Discriminant Function; *MAL* = Malingering Index; *RDF* = Rogers Discriminant Function; *SPI* = Suicide Potential Index; *VPI* = Violence Potential Index; *TPI* = Treatment Potential Index; ALCest = Alcohol estimate; DRGest = Drug estimate; MCE = Mean Clinical Elevation.

Predicting time to first treatment noncompliance using the COMPAS recidivism scales and the PAI treatment scales yielded slightly different results. Cox proportional-hazards regression model, predicting time to first incident of treatment noncompliance from the COMPAS recidivism scales was statistically significant (Table 17). Of the COMPAS recidivism scales, the COMPAS GRR scale was statistically significant, indicating an increase of one score on GRR increased the hazard of treatment noncompliance by a factor of 1.34, or 29% (Table 18).

Table 17.

Chi-square Values for Cox Regression Predicting Noncompliance using the COMPAS and the PAI

	χ^2 Model			χ^2 Difference		
Model	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Noncompliance ~ COMPAS + PAI Treatment Scales	10.68	7	.15	–	–	–
Noncompliance ~ COMPAS	8.25	2	**.02**	2.43	5	.79

Note. N = 84.
Analysis with pooled imputed data.

Table 18.

Cox Regression Predicting Time to Noncompliance using the COMPAS and the PAI

	B (SE)	HR	*LL*	*UL*	*p*
Noncompliance ~ COMPAS					
GRR (COMPAS)	.29 (.13)	1.34	1.03	1.74	**.03**
VRR (COMPAS)	-.01 (.14)	.99	0.75	1.30	.92
Noncompliance ~ COMPAS + PAI Treatment Scales					
GRR (COMPAS)	.30 (.14)	1.35	1.01	1.81	**.04**
VRR (COMPAS)	-.02 (.14)	.98	0.73	1.32	.90
AGG (PAI)	.00 (.02)	1.00	0.97	1.03	.96
SUI (PAI)	.01 (.01)	1.01	0.98	1.03	.62
STR (PAI)	-.02 (.02)	0.98	0.94	1.02	.31
NON (PAI)	.01 (.02)	1.01	0.98	1.04	.58
RXR (PAI)	-.02 (.02)	0.98	0.94	1.02	.23

Note. N = 84. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; GRR = General Recidivism Risk; VRR = Violent Recidivism Risk; *AGG* = Aggression; *SUI* = Suicidal Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection.
Analysis with pooled imputed data. Appendix D shows results after listwise deletion for comparison.

The addition of the PAI treatment scales on step two did not improve the model at a statistically significant level, suggesting the PAI treatment scales did not provide incremental validity over the COMPAS GRR.

Cox proportional-hazards regression model, predicting time to first treatment noncompliance using the COMPAS recidivism scales and the VRAG was statistically significant (Table 19). However, only the COMPAS GRR predicted treatment compliance at a statistically significant level, indicating an increase of one score on GRR increased the hazard of treatment noncompliance by a factor of 1.34, or 29%. The addition of the VRAG to the model did not provide incremental validity above the COMPAS GRR.

Table 19.

Chi-square Values for Cox Regression Predicting Noncompliance using the COMPAS and the VRAG

Model	χ^2 Model			χ^2 Difference		
	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Noncompliance ~ COMPAS + VRAG	10.62	3	**.01**	–	–	–
Noncompliance ~ COMPAS	8.25	2	**.02**	2.37	1	.12

Note. N = 84.
Analysis with pooled imputed data.

Table 20.

Cox Regression Estimates Predicting Noncompliance Using the COMPAS and the VRAG

	B (SE)	HR	*LL*	*UL*	*p*
Noncompliance ~ COMPAS					
GRR (COMPAS)	.29 (.13)	1.34	1.03	1.74	**.03**
VRR (COMPAS)	-.01 (.14)	.99	0.75	1.30	.92
Noncompliance ~ COMPAS + VRAG					
GRR (COMPAS)	.28 (.14)	1.32	1.01	1.76	**.05**
VRR (COMPAS)	-.03 (.14)	.97	.72	1.29	.81
VRAG	.13 (.15)	1.14	.84	1.55	.40

Note. N = 84. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; GRR = General Recidivism Risk; VRR = Violent Recidivism Risk; VRAG = Violence Risk Appraisal Guide Risk Category.
Analysis with pooled imputed data. Appendix E shows results after listwise deletion for comparison.

Analysis 3

The third analysis identified PAI profiles that predict various types of treatment noncompliance. First, the relationships between demographic variables with components of treatment noncompliance were examined to see the extent to which static factors correlated with treatment noncompliance. Table 21 shows that age, age at first offense, and the number of prior arrests correlated negatively with treatment noncompliance at a statistically significant level. However, the demographic variables show minimal relationship with custodial remand, receiving new charges or being hospitalized.

Table 21.

Correlations of Demographics by Treatment Noncompliance

	VOC	Remanded	New Charge	Hospitalized
Age	-.22*	-.13	-.20	.14
Gender	-.02	.12	-.02	-.01
Minority	.09	.10	.18	-.12
Number of Prior Arrests	-.22*	.19	.09	.12
Age at First Arrest	-.23*	-.17	-.13	.08

Note. N = 84; VOC = Violation of Conditions.
* $p < .05$.

Furthermore, gender and minority status also showed minimal relationship with treatment noncompliance.

Bivariate correlations of the PAI scales with each component of treatment noncompliance show that having problematic antisocial personality traits, substance abuse, and difficulties managing anger, positively correlated with treatment noncompliance at a statistically significant level (Table 22). Having antisocial personality traits, substance abuse, and difficulties managing anger also correlated positively with custodial remands at a statistically significant level. Only having antisocial personality traits correlated positively with new arrests at a statistically significant level. Consistent with the results from the first analysis, none of the clinical scales demonstrated associations with treatment noncompliance. In addition, only the PAI scales correlated with hospitalization was alcohol abuse.

Table 22.

Correlations of PAI Scales by Treatment Noncompliance

	VOC	Remanded	New Charge	Hospitalized
SOM	.02	.00	-.06	.10
ANX	.00	.06	-.00	-.08
ARD	.01	-.08	-.01	-.07
DEP	.09	.06	.03	-.09
MAN	.06	-.01	.22	-.12
PAR	-.01	-.11	.14	-.16
SCZ	.12	-.01	.16	-.10
BOR	.17	.16	.18	-.16
ANT	**.37***	**.28***	**.35***	-.04
ALC	**.23***	**.26***	.05	**.22***
DRG	**.45***	**.41***	.26	.16
AGG	**.27***	**.25***	.13	-.08
SUI	.15	.13	.12	.05
STR	.07	-.02	-.00	-.12
NON	.14	.01	.14	.00
RXR	-.17	-.19	-.04	.02
DOM	-.05	-.11	-.04	.09
WRM	.08	.04	.08	.12

Note. N = 84; *SOM* = Somatic Complaints; *ANX* = Anxiety; *ARD* = Anxiety-Related Disorder; *DEP* = Depression; *MAN* = Mania; *PAR* = Paranoia; *SCZ* = Schizophrenia; *BOR* = Borderline Features; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression; *SUI* = Suicide Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection; *DOM* = Dominance; *WRM* = Warmth; VOC = Violation of Conditions.
* $p < .05$.

An examination for bivariate correlations of the PAI subscales with different treatment noncompliance show that the subcomponents of antisocial personality traits (i.e., antisocial behaviors, egocentricity, stimulus seeking), aggression (i.e., aggressive attitude, verbal aggression, physical aggression) are statistically significantly correlated with noncompliance. In addition, personality traits associated with such behaviors such as impulsivity and grandiosity were also correlated with noncompliance. The ARD-O subscale, which assesses obsessive-compulsive thoughts and behaviors, was negatively correlated with remands. These correlations suggest the PAI scales may provide additional information related to treatment noncompliance to the demographic variables.

Table 23.

Correlations of PAI Subscales by Treatment Noncompliance

	VOC	Remanded	New Charge	Hospitalized
SOM-C	-.04	.00	-.13	.18
SOM-S	.02	.00	-.02	.04
SOM-H	-.03	-.01	-.06	.13
ANX-C	.01	.07	.03	.02
ANX-A	-.01	.09	-.01	.01
ANX-P	-.04	.04	-.07	.01
ARD-O	-.08	**-.24***	-.03	-.06
ARD-P	.12	.12	.11	.10
ARD-T	-.05	-.06	-.11	.01
DEP-C	.13	.11	.03	-.05
DEP-A	.07	.01	.02	-.08
DEP-P	-.01	.01	-.02	.07
MAN-A	.06	-.07	.14	-.16
MAN-G	.09	-.02	**.22***	.02
MAN-I	.01	.04	.11	-.08
PAR-H	-.12	-.21	.04	-.09
PAR-P	.03	-.02	.19	-.10
PAR-R	.09	-.05	.09	-.05
SCZ-P	.14	.00	**.25***	-.05
SCZ-S	.04	-.05	.06	-.06
SCZ-T	.07	.07	.07	-.01
BOR-A	.08	.16	.11	-.16
BOR-I	.03	.05	.07	-.12
BOR-N	.07	.05	.05	.00
BOR-S	**.43***	**.39***	**.27***	.06
ANT-A	**.39***	**.31***	**.22***	.06
ANT-E	**.25***	.08	**.26***	-.09
ANT-S	**.30***	**.28***	**.37***	-.08
AGG-A	**.21**	**.25***	.04	.01
AGG-V	.12	.19	**.25***	-.11
AGG-P	**.32***	**.28***	.09	.01

Note. N = 84; *SOM-C* = Conversion; *SOM-S* = Somatization; *SOM-H* = Health Concerns; *ANX-C* = Cognitive; *ANX-A* = Affective; *ANX-P* = Physiological; *ARD-O* = Obsessive-Compulsive; *ARD-P* = Phobias; *ARD-T* = Traumatic Stress; *DEP-C* = Cognitive; *DEP-A* = Affective; *DEP-P* = Physiological; *MAN-A* = Activity Level; *MAN-G* = Grandiosity; *MAN-I* = Irritability; *PAR-H* = Hypervigilance; *PAR-P* = Persecution; *PAR-R* = Resentment; *SCZ-P* = Psychotic Experiences; *SCZ-S* = Social Detachment; *SCZ-T* = Thought Disorder; *BOR-A* = Affective Instability; *BOR-I* = Identity Problems; *BOR-N* = Negative Relationships; *BOR-S* = Self-Harm; *ANT-A* = Antisocial Behaviors; *ANT-E* = Egocentricity; *ANT-S* = Stimulus Seeking; *AGG-A* = Aggressive Attitude; *AGG-V* = Verbal Aggression; *AGG-P* = Physical Aggression; VOC = Violation of Conditions.
$^{*}p < .05$.

Poisson regression model predicting number of treatment violations using the PAI BOR-S, ANT, ALC, DRG, and AGG scales show that the overall model was statistically significant, $\chi^2(5, N = 84) = 28.29, p < .001$. An increase of one T score on DRG increased the estimated count of treatment noncompliance increases by a factor of 1.03 (Table 24).

Table 24.

Poisson Regression Estimates Predicting Number of VOC from the PAI

	B (SE)	Wald	*df*	*p*
BOR-S	-.01 (.01)	1.02	1	.31
ANT	.02 (.01)	2.91	1	.09
ALC	-.01 (.01)	.88	1	.35
DRG	.03 (.01)	13.45	1	**<.001**
AGG	-.01 (.01)	.63	1	.43

Note. *N* = 84. *BOR-S* = Self-Harm; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression.

The linear regression model, predicting the severity of treatment violations using the PAI BOR-S, ANT, ALC, DRG, and AGG scales, shows that the overall model was statistically significant, $F(5, 78) = 4.15$, $p = .002$, and accounted for 21% of the variance. Only drug problems (DRG) predicted the severity of treatment violations at a statistically significant level, indicating an increase of one score on DRG increased the severity of treatment violation by .08 (Table 25).

Table 25.

Regression Estimates Predicting Severity of VOC from the PAI

	B	(SE)	*Beta*	*t*	*p*
BOR-S	-.02	.03	-.11	-.74	.46
ANT	.05	.03	.22	1.51	.14
ALC	-.03	.02	-.14	-1.20	.24
DRG	.08	.03	.50	3.09	**.003**
AGG	-.01	.03	-.06	-.46	.65

Note. $N = 84$. *BOR-S* = Self-Harm; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression. Appendix F shows the results of predicting the severity of VOC from the PAI scales after excluding VOCs as a result of positive toxicology

Given that the same scales (i.e., BOR-S, ANT, ALC, DRG, and AGG) were associated with different components of treatment noncompliance, a Noncompliance Index (NI) was created from of the sum of above mentioned scales with clinically significant elevations (i.e., BOR-S, ANT $\geq$ 70T, ALC $\geq$ 70T, DRG $\geq$ 70T, and AGG $\geq$ 70T), rather than the improvement in model fit of Cox regression models. The NI was created using clinically significant T scores (i.e., 2 *SD* above the normative sample) of PAI scales rather than using statistically significant weighing of each PAI scale based on the parameter estimates using regression for practical ease. ROC analysis of the NI yielded AUC of .70, 95% CI [.59 – .81], $p < .001$ for VOC, AUC of .72, 95% CI [.59 – .84], $p < .001$, for custodial remands, and AUC of .60, 95% CI [.44 – .75], $p = .22$ for defendants who receive new charges. They show that defendants who have difficulty with treatment compliance, on average had higher scores on the NI than the defendants who completed the treatment mandate without difficulties.

CHAPTER IV

Discussion

The first analysis of this study examined three explanations for the overrepresentation of the mentally ill in the criminal justice system: the criminalization model, the criminological model, and the social/personality model. The results of the first analysis suggest strict interpretation of the criminalization model is not supported. Cox regression models show that the clinical and criminological variables did not predict treatment noncompliance at a statistically significant level. In fact, only the social/personality variables, specifically having antisocial personality features related to a history of illegal activities, egocentrism, instability and recklessness, predicted treatment noncompliance at a statistically significant level. The social/personality variables outperformed both the clinical and criminological variables for predicting treatment noncompliance. The results of the first analysis provide partial support for the hypothesized modified criminalization model described in Figure 4, in which the social/personality variables have main effects on noncompliance.

The implication is that treatment for defendants with mental illness must not only target clinical symptoms, but also reduce personality characteristics associated with treatment noncompliance. Only ensuring medication compliance and managing clinical symptoms are not enough to mitigate recidivism. Mentally ill defendants require multi-faceted treatment designed to target antisocial cognition, in addition to medication management, substance abuse treatment, and therapy. Although the criminological variables did not appear to directly affect treatment noncompliance in this study, they may indirectly affect treatment noncompliance by affecting antisocial cognition or behavior. Therefore, careful examination of economic, social, and cognitive precipitants of unlawful behavior remains important aspects of reducing treatment noncompliance and recidivism.

Although a relationship between clinical symptoms and noncompliance was anticipated in the hypothesis, the lack of relationship between clinical symptoms and treatment noncompliance does not support the commonly touted explanation for the increased incarceration of the mentally ill. Rather, the results add to the literature in support of the RNR model, in which assessing and modifying the criminological and social/personality needs are essential to the treatment and recovery of defendants with mental illness. The RNR model applies cognitive social learning based interventions to target problematic thinking patterns and behaviors. The interventions that have shown effectiveness include Thinking for a Change (Bush, Glick, & Taymans, 2011), Moral Recognation Therapy (Little & Robinson, 1988), and Reasoning and Rehabilitation (Ross, Fabiano, & Ewles, 1988). The results of this study further support the need to target antisocial thinking and personality patterns. Queens TASC utilizes journaling based on cognitive behavioral interventions with all the defendants who accepted pleas.

Another explanation is the inadequate power necessary to find the relationship between the clinical symptoms and noncompliance. Although many of the PAI clinical scales did not have statistically significant correlations with noncompliance, some of the clinical scales showed a trend toward statistical significance. A larger sample would likely have adequate power for these correlations to achieve statistical significance. Although the strict interpretation of the criminalization hypothesis is not supported by the results of this study, the limited statistical power does not rule out possibility that the criminalization model may apply in other contexts or in a less strict form.

The PAI profiles of the defendants accepted for jail diversion appear to closely approximate the clinical normative sample, rather than the community standardization sample or the correctional sample, regardless of whether they completed the court mandate or failed. Even the defendants who were referred for diversion but were subsequently rejected produced PAI profiles comparable to the clinical normative sample. The fact that the PAI profiles closely approximated the clinical norms, in comparison to the standardized sample and the correctional sample, on each of the 22 scales suggests that the defendants who were referred to TASC for diversion resemble mentally ill patients more than prisoners or community members.

The finding that the variables associated with the social/personality hypothesis predicted treatment noncompliance at a statistically significant level, is consistent with the literature that explains the overrepresentation of the mentally ill in the criminal justice system as a result of thinking styles condoning or accepting of antisocial activities (Carr et al., 2009; Rotter et al., 2005; Walters, 1990) and having criminal associates (Andrews, Bonta, & Wormith, 2006). The finding that the PAI antisocial personality features scale predicted treatment noncompliance is also consistent with the finding that the Historical–Clinical–Risk Management–20 (HCR-20; Webster, Douglas, Eaves, & Hart, 1997) and the PCL:SV were predictive of diversion noncompliance and reincarceration (Barber-Rioja, 2009; Barber-Rioja, Dewey, Kopelovich, & Kucharski, 2012). It provides converging evidence that certain cluster of problematic personality traits affect noncompliance and recidivism beyond untreated clinical symptoms.

Furthermore, the finding in Barber-Rioja et al. (2012) that the dynamic clinical items predicted treatment noncompliance at 3 months and the dynamic risk items predicted noncompliance at 6- and 12-month follow-ups, also sheds light on why the VRAG was not a good predictor of noncompliance in this study. The VRAG items are similar to the historical items on the HCR-20. Therefore, the VRAG failing to predict treatment noncompliance in this study converges with the finding in Barber-Rioja et al. (2012) that the historical items on the HCR-20 were not useful for predicting noncompliance.

The second analysis shows that, contrary to hypothesis that the PAI treatment scales or the VRAG provides incremental validity to the COMPAS alone for predicting treatment mandate completion, none of the measures used in the study predicted diversion mandate outcome. The COMPAS GRR, or general recidivism risk, scale predicted time to treatment noncompliance. The addition of the PAI treatment scales or the VRAG did not improve predictive validity over the COMPAS. Although opaque in its development and construction, the COMPAS GRR appears to demonstrate predictive validity for treatment noncompliance above and beyond the PAI and the VRAG. The results of this study support the use of the COMPAS for jail diversion evaluations. In fact, further study of the COMPAS GRR scale is warranted to examine how it predicted treatment noncompliance, particularly because it was not designed to be a predictor of mandate outcome.

Despite the criticisms that have been raised about the COMPAS, the GRR scale outperforming the VRR, is consistent within its limited literature. The reason why the VRR and the VRAG performed poorly is likely due to a low-base event. As indicated in the literature, most mentally ill offenders do not commit violent crimes; they are more likely arrested for substance-related offenses or non-violent property crimes. The base-rate of violent crime is low; examining the rate of violent offenses within the mentally ill sample is a subsample of an already low base-rate. Furthermore, the defendants who are referred for jail diversion may already be pre-screened such that they are not at high risk for violent recidivism. Therefore, the measures used to predict violent recidivism may simply be examining a phenomenon that rarely occurs, even within this population.

The third analysis shows that the same grouping of personality characteristics, (i.e., impulsivity, antisocial personality traits, substance abuse, and aggression) correlated with different components of treatment noncompliance. This grouping of personality tendencies and behavioral patterns are characteristic of individuals who exhibit Antisocial Personality Disorder. For example, individuals who have difficulties with authority and following rules, irresponsible, egocentric, reckless, and impulsive also tend to engage in substance abuse and react in aggressive ways. ROC analyses found that defendants who violated treatment conditions, received custodial remands, and received new charges, on average yielded higher score on the Noncompliance Index than the defendants who did not have difficulty with treatment compliance. Furthermore, the DRG, or drug problems, scale predicted both the frequency and the severity of treatment violations.

The PAI shows promise as a tool for assessing defendants referred for jail diversion. The PAI profiles of the defendants accepted for diversion approximated the clinical norm on almost all 22 scales. This shows that the defendants who were to TASC referred for diversion appear similar to mentally ill patients, rather than prisoners or community members. It also provides preliminary support for the use of the PAI for jail diversion purposes. A possible future direction is to continue the collection of PAI data in this population with the intent to conduct multiple group analysis to show measurement invariance. This would permit the already developed PAI clinical norm be applied for diversion purposes without needing to create new normative samples. This would allow mental health professional evaluating defendants for diversion to quickly assess whether they report psychiatric symptoms consistent with other clinical patients. Therefore the defendants who do not produce such profiles indicative of elevation on the clinical scales necessitate further evaluation to assess for the presence of mental illness and eligibility for diversion. Even without the benefit of the clinical norm, the PAI enables mental health professions to assess the defendants' response style and see whether their reported symptoms match with their documented psychiatric history and presenting symptoms. Another direction is to develop local norms for each of the diversion sites. Local norms offer the practical advantage of allowing individual diversions sites to compare referred defendants to defendants who have completed or struggled with the treatment mandate. However, creating locals norms often require sample sizes in the thousands, which requires extensive time and resources.

Several limitations in this study need discussion. First, after removing invalid cases due defendants taking alternative dispositions to diversion, inconsistent responding response style, the number of cases available for analyses was 84, which was fewer than the originally intended 125. Having fewer available cases for analysis reduced power for some of the analyses. Power analysis showed that a sample of 125 cases could detect a 10% increase in treatment failure with difference of 1/2 SD. The 84 defendants who were accepted by TASC for jail diversion differed by one-tenth to two-tenths of a SD on the scales of interest with respect to mandate status, which achieved power of 0.24 and 0.28 respectively. Even if the intended 125 cases were available, differences of one-tenth to two-tenths of a SD would have achieved powers of 0.56 and 0.65 respectively. Future studies that include larger sample sizes will have higher power to differentiate defendants who complete and fail treatment mandate. In addition, studies with larger sample sizes may take advantage of latent variable modeling techniques that allow for a more direct test of the different models of criminal behavior than a series of regression analyses. Nevertheless, if the differences in profile remain one-tenth to two-tenths of a SD between the different mandate status, studies will need sample sizes of over approximately 680 (for a one-tenth of a SD difference) to 190 (for a two-tenths of a SD difference) to achieve statistical significance at .05 alpha.

The low statistical power may have also hindered the ability to find relationship between the clinical symptoms and noncompliance. Although many of the PAI clinical scales did not have statistically significant correlations with noncompliance, some of the clinical scales showed a trend toward statistical significance. A larger sample would likely have adequate power for these correlations to achieve statistical significance, which may support the criminalization hypothesis.

Second, although the VRAG has been documented in a few studies to show effectiveness for predicting general recidivism, it remains primarily an assessment of violent recidivism. Violent recidivism is one form of treatment noncompliance that would violate a treatment mandate, but it is not the most common way. Most defendants violated the terms of their treatment mandate by testing positive on urine toxicology or complying poorly with treatment program rules, rather than reoffending. This could have contributed to the poor predictive validity of the VRAG and the COMPAS VRR. In addition, there is no mechanism for follow up with defendants after their treatment mandate ends. Instruments like the VRAG assess the likelihood of recidivism after seven years and after 10 years. Perhaps it is premature to assess the predictive accuracy of the VRAG when defendants can only be followed-up during the mandate. However, from a cost-benefit analysis perspective, every year that inpatient or custodial treatment can be diverted to community-based treatment saves resources for the state. Researchers conducting future research may want to include a longer follow-up periods because recidivism may increase as defendants remain in the community for longer periods of time and have more opportunities to reoffend.

Third, the defendants referred to TASC for diversion do not represent the typical forensic sample. As indicated in the sample description, the defendants referred to TASC appear more similar to the population of Queens County than an average jail or prison sample. In addition, the defendants accepted for diversion at Queens TASC Mental Health Diversion Program generally have more years of education, later age of first arrest, fewer prior arrests and convictions, than the typical forensic population.

Fourth, similar to the majority of the literature on mental health courts and jail diversion programs, the results of this study are within the limits of the U.S. Information pertaining to the existence of mental health court and diversion programs, in addition to the clinical and public safety outcomes of these programs remain relatively unknown. A recent whitepaper summarizing the 10 years outcomes of Portugal's decriminalization of all drugs later found that drug usage rates have remained similar to pre-decriminalization and that some metrics showed that drug usage even decreased compared to other European countries that adopt harsher criminalization approaches (Greenwald, 2009). Greenwald (2009) argued that since decriminalization, the prevalence rates of drug usage have decreased significantly in Portugal, most notably in the adolescent age groups, from approximately 14% to 11% for ages 13 to 15, and from 28% to 22% for ages 16 to 19. The total number of drug-related deaths, mortality rates, and newly reported cases of HIV and AIDS infections among drug users has all decreased. Compared to other European countries in the European Union (EU), the lifetime prevalence rates of drug use in post-decriminalization Portugal are half of the rates of the majority of countries within the EU, especially in states that adopt more criminalized approaches (Greenwald, 2009). Nevertheless, very little is known about the approach and outcomes that other countries have taken to ease the burden of treat defendants with mentally illness.

Fifth, the models of criminal behavior examined in this study are simplifications of human behavior. Although clinical, criminological, and social/personality factors have been identified as the major plausible explanations for why defendants may not comply with treatment, they are not the only factors that lead individuals to treatment noncompliance. In describing why complex systems fail, Cook (2000, p.1) stated, "catastrophe requires multiple failures – single failures are not enough." Cook referred to complex social systems with his statement, but his point about there being multiple underlying explanations for catastrophic negative events to occur is analogous to why multiple explanations may underlie treatment noncompliance. Even when we attempt to infer the precipitants of treatment noncompliance by examining thoughts and behavior patterns before treatment noncompliance, we are only assessing a fraction of the cognitions and motivators that are observable and within awareness. There may be other thought patterns or behavioral contingencies for which neither the defendant nor the evaluator is aware. Furthermore, even within the same individual, the explanations underlying one incidence of treatment noncompliance may not be the same as the explanations for another.

Despite these limitations, this study shows that the COMPAS and the PAI can predict treatment noncompliance fairly well, even if they cannot predict treatment mandate outcome. This enables evaluators to better identify the defendants who have good chances of completing court mandated treatment and the defendants who may have more trouble adhering to the treatment mandate. In addition, the results of this study support the existing literature on the need to attend to criminological and social/personality factors in understanding noncompliance and recidivism.

Appendix A

PAI Raw Scale Scores of the Normative Samples

	Standardization Sample[a]			Clinical Sample[b]			Corrections Sample[c]		
Scale	*M*	*SD*	*α*	*M*	*SD*	*α*	*M*	*SD*	*α*[d]
Validity									
ICN	5.39	3.35	.45	6.57	3.04	.23	6.70	2.94	–
INF	2.66	2.57	.52	3.18	2.47	.40	4.22	2.45	–
NIM	1.69	2.70	.72	4.38	4.27	.74	2.98	3.56	.77
PIM	15.07	4.36	.71	12.24	5.07	.77	14.48	5.43	.81
Clinical									
SOM	11.09	10.07	.89	19.34	14.39	.92	12.56	10.17	.87
ANX	16.47	10.56	.90	28.50	12.39	.94	19.40	11.92	.92
ARD	19.91	8.30	.76	28.27	13.39	.86	24.27	10.56	.83
DEP	14.28	9.43	.87	27.38	15.10	.93	19.05	11.42	.90
MAN	23.01	9.22	.82	25.34	10.15	.82	26.98	10.89	.83
PAR	18.45	8.69	.85	24.86	11.44	.89	25.62	9.70	.84
SCZ	13.99	7.79	.81	21.03	11.79	.89	16.49	10.33	.89
BOR	18.03	10.00	.87	31.39	13.85	.91	27.65	12.71	.90
ANT	13.16	9.11	.84	18.88	11.37	.86	24.18	10.00	.82
ALC	4.83	5.62	.84	10.44	10.53	.93	8.95	8.62	.91
DRG	4.09	4.99	.74	8.62	8.91	.89	16.51	9.59	.90
Treatment									
AGG	14.81	5.42	.85	19.69	11.18	.90	17.50	10.36	.90
SUI	3.28	4.86	.85	9.09	9.42	.93	3.20	4.53	.90
STR	5.80	4.45	.76	11.91	5.75	.79	10.78	5.51	.77
NON	4.90	3.67	.72	8.44	5.13	.80	6.40	4.58	.78
RXR	13.76	4.65	.76	9.10	5.45	.80	9.16	4.92	.76
Interpersonal	20.60	5.59	.78	19.41	6.49	.82	22.77	5.62	.79
DOM									
WRM	23.58	5.63	.79	21.16	6.60	.83	23.60	5.68	.75
Supplemental									
MAL	0.53	0.78	–	0.80	0.98	–	–	–	–
RDF	-1.00	1.08	–	-1.15	1.17	–	–	–	–
DEF	3.07	1.60	–	1.75	1.56	–	–	–	–
CDF	138.14	14.91	–	135.28	18.79	–	–	–	–
SPI	3.14	3.25	–	7.85	5.35	–	–	–	–
VPI	1.58	2.18	–	4.40	3.98	–	–	–	–
TPI	1.12	1.90	–	3.86	3.22	–	–	–	–

Note. ICN = Inconsistency; *INF* = Infrequency; *NIM* = Negative Impression Management; *PIM* = Positive Impression Management; *SOM* = Somatic Complaints; *ANX* = Anxiety; *ARD* = Anxiety-Related Disorder; *DEP* = Depression; *MAN* = Mania; *PAR* = Paranoia; *SCZ* = Schizophrenia; *BOR* = Borderline Features; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression; *SUI* = Suicide Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection; *DOM* = Dominance; *WRM* = Warmth; *MAL* = Malingering Index; *RDF* = Rogers Discriminant Function; *DEF* = Defensive Index; *CDF* = Cashel Discriminant Function; *SPI* = Suicide Potential Index; *VPI* = Violence Potential Index; *TPI* = Treatment Process Index.
[a]*N* = 1,000. [b]*N* = 1,246. [c]*N* =1,155. [d]*N* = 695; Reliability data reproduced from Edens and Ruiz (2005).
The supplemental estimated ALC, estimated DRG, and Mean Clinical Elevation scales are only calculated from T scores.
The supplemental scales were not calculated in the corrections normative sample.

Appendix B

Cox Regression Model Predicting Noncompliance Using Clinical and Criminological Factors after Listwise Deletion

	χ^2_{Model}			$\chi^2_{Difference}$		
Model	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Noncompliance ~ Clinical + Criminological	9.27	5	.10	–	–	–
Noncompliance ~ Clinical	0.21	1	.65	9.06	4	.06

	B (SE)	HR	*LL*	*UL*	*p*
Model 1: Noncompliance ~ Clinical					
MCE (Clinical)	.01 (.02)	1.01	.97	1.04	.65
Model 2: Noncompliance ~ Clinical + Criminological					
MCE (Clinical)	.02 (.02)	1.02	.98	1.07	.34
Criminogenic Need (Criminological)	.15 (.14)	1.16	.89	1.52	.28
Lifestyle (Criminological)	.17 (.13)	1.19	.92	1.53	.18
Family (Criminological)	-.43 (.17)	0.65	.47	.90	.01
Social Exclusion (Criminological)	.30 (.17)	1.43	.97	1.89	.07

Note. *N* = 57. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; MCE = Mean clinical elevation.

The non significant χ^2_{Model} and $\chi^2_{Difference}$ are similar to results conducted with multiple imputation reported in Table 8 and Table 9. Although the Family (Criminological) predictor has a statistically significant *p*-value, it is not interpreted because the overall model is not statistically significant.

Appendix C

Cox Regression Model Predicting Noncompliance Using Clinical and Social/Personality Factors after Listwise Deletion

	χ^2_{Model}			$\chi^2_{\text{Difference}}$		
Model	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Noncompliance ~ Clinical + Social/Personality	5.29	4	.26	–	–	–
Noncompliance ~ Clinical	0.21	1	.65	5.08	3	.17

	B (SE)	HR	*LL*	*UL*	*p*
Model 1: Noncompliance ~ Clinical					
MCE (Clinical)	.01 (.02)	1.01	.97	1.05	.65
Model 2: Noncompliance ~ Clinical + Social/Personality					
MCE (Clinical)	.04 (.03)	1.04	.99	1.09	.13
BOR (Social/Personality)	-.05 (.03)	.96	.90	1.01	.13
ANT (Social/Personality)	.04 (.02)	1.05	1.00	1.09	.05
Personality (Social/Personality)	-.11 (.11)	.89	.71	1.12	.32

Note. N = 57. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; MCE = Mean Clinical Elevation; *BOR* = Borderline Personality Traits; *ANT* = Antisocial Personality Traits.

The non significant χ^2_{Model} and $\chi^2_{\text{Difference}}$ are different than results conducted with multiple imputation reported in Table 10 and Table 11. Although the most likely reason is a reduction in statistical power due to having fewer cases, the difference could also reflect a bias in the cases that were eliminated due to the pattern of missing data. Correlation analysis of the missing data with demographic variables, clinical outcomes, the PAI, and the VRAG shows that missing the COMPAS was negatively correlated with years education at a statistically significant level.

Appendix D

Cox Regression Predicting Noncompliance using the COMPAS and the PAI after Listwise Deletion

	χ^2 Model			χ^2 Difference		
Model	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Noncompliance ~ COMPAS + PAI Treatment Scales	19.76	7	**.01**	–	–	–
Noncompliance ~ COMPAS	9.47	2	**.01**	10.29	5	.08

	B (SE)	HR	*LL*	*UL*	*p*
Noncompliance ~ COMPAS					
GRR (COMPAS)	.35 (.12)	1.42	1.13	1.80	**.003**
VRR (COMPAS)	-.28 (.12)	.76	0.59	.98	**.03**
Noncompliance ~ COMPAS + PAI Treatment Scales					
GRR (COMPAS)	.30 (.14)	1.35	1.01	1.81	**.04**
VRR (COMPAS)	-.02 (.14)	.98	0.73	1.32	.90
AGG (PAI)	.00 (.02)	1.00	0.97	1.03	.96
SUI (PAI)	.01 (.01)	1.01	0.98	1.03	.62
STR (PAI)	-.02 (.02)	0.98	0.94	1.02	.31
NON (PAI)	.01 (.02)	1.01	0.98	1.04	.58
RXR (PAI)	-.02 (.02)	0.98	0.94	1.02	.23

Note. *N* = 57. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; GRR = General Recidivism Risk; VRR = Violent Recidivism Risk; *AGG* = Aggression; *SUI* = Suicidal Ideation; *STR* = Stress; *NON* = Nonsupport; *RXR* = Treatment Rejection.

The significant χ^2_{Model} values are slightly different than the results conducted with multiple imputation reported in Table 17 and Table 18. Similar to the results from using multiple imputation, the initial model consisting of only COMPAS predictors is statistically significant. The difference is that the overall model remains statistically significant in this analysis, even though the addition of the PAI treatment scales do not improve the model. This does not change the interpretation that the COMPAS GRR remains a statistically significant predictor of treatment noncompliance, but the addition of the PAI treatment scales do not aid the prediction of noncompliance.

Appendix E

Cox Regression Predicting Noncompliance Using the COMPAS and the VRAG after Listwise Deletion

Model	χ^2_{Model}			$\chi^2_{Difference}$		
	χ^2_M	df_M	p	$\Delta\chi^2$	Δdf	p
Mandate Status ~ COMPAS + VRAG	13.11	3	**.004**	–	–	–
Mandate Status ~ COMPAS	9.47	2	**.009**	3.64	1	.06

	B (SE)	HR	*LL*	*UL*	*p*
Model 1: Mandate Status ~ COMPAS					
GRR (COMPAS)	.35 (.12)	1.42	1.13	1.80	**.003**
VRR (COMPAS)	-.28 (.12)	.76	0.59	.98	**.03**
Model 2: Mandate Status ~ COMPAS + VRAG					
GRR (COMPAS)	-.55 (.17)	1.73	1.24	2.41	**.001**
VRR (COMPAS)	-.32 (.14)	.72	.55	.96	**.02**
VRAG	-.07 (.23)	.93	.60	1.45	.74

Note. N = 57. *LL* = Lower Limit; *UL* = Upper Limit; HR = Hazard Ratio; GRR = General Recidivism Risk; VRR = Violent Recidivism Risk; VRAG = Violence Risk Appraisal Guide Risk Category.

The significant χ^2_{Model} values are similar to the results conducted with multiple imputation reported in Table 19 and Table 20. The initial model consisting of only COMPAS predictors is statistically significant. The overall model remains statistically significant, even though the addition of the VRAG does not improve the model. Although the *p*-value for $\chi^2_{Difference}$ shows a stronger trend toward statistical significance in this analysis, nonetheless, the interpretation remains unchanged.

Appendix F

Regression Estimates Predicting Severity of VOC from PAI after Removing VOC due to Positive Toxicology

	B	(SE)	*Beta*	*t*	*p*
BOR-S	-.01	.03	-.07	-.50	.62
ANT	.04	.03	.19	1.33	.19
ALC	-.02	.02	-.13	-.96	.34
DRG	.07	.03	.47	2.91	**.005**
AGG	-.01	.03	-.06	-.46	.65

Note. N = 84.
BOR-S = Self-Harm; *ANT* = Antisocial Features; *ALC* = Alcohol Problems; *DRG* = Drug Problems; *AGG* = Aggression.
$F(5, 78) = 3.93$, $p = .003$.

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