2006

Predicting Institutional Adjustment with the Psychological Inventory of Criminal Thinking Styles and the Psychopathology Checklist : Screening Version

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PREDICTING INSTITUTIONAL ADJUSTMENT WITH THE PSYCHOLOGICAL INVENTORY OF CRIMINAL THINKING STYLES AND THE PSYCHOPATHY CHECKLIST: SCREENING VERSION

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Submitted in Partial Fulfillment of the Requirements of the Degree of

Doctor of Psychology

July 2006

PHILADELPHIA COLLEGE OF OSTEOPATHIC MEDICINE
DEPARTMENT OF PSYCHOLOGY

Dissertation Approval

This is to certify that the thesis presented to us by Wanda Mandell *on the* 5TH *day of* December*, 20*05*, in partial fulfillment of the requirements for the degree of Doctor of Psychology, has been examined and is acceptable in both scholarship and literary quality.*

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Acknowledgements

Arriving at this point in my academic career is due in very large part to the influences and affiliations that touched my life particularly over the last 5 years.

I would like to express my professional indebtedness to my committee members. Thank you to Dr. Fred Rotgers for initiating the spark for undertaking this study and for providing instruction and technical direction throughout the course of this project. Thank you to Dr. Robert DiTomasso for being a positive support and being there with the right answers at the right time. An extra special indebtedness and gratitude goes to Dr. Glenn Walters for his unending support from inception to completion. His prompt, patient, and thought provoking responses to my many queries were the force that helped me to maintain an unwavering perseverance. Some of the territory in this project was 'uncharted' and was similar to my making a sojourn in an alien place—complete with monsters to slay. Because of his respectful guidance, and expertise, Dr. Walters helped me conquer the seemingly unconquerable.

I would like to extend indebtedness to my two practicum supervisors for keeping me on course and grounded throughout the process. Thank you to Dr. Gary Londis for providing confidence and buttressing me through the initial days of this project and for the continuous check ups, equipped with gentle nudges and humor, that caringly kept me steady and on track. Additionally, a very big thank you goes to him for acting as an alternate rater in this study. A heartfelt thank you goes to Dr. Fred Gimino for his unending balance of patience, concern, and humor. He became my soundboard while I slew one monster after another. Without his objectivity, empathy, and discrimination I might have slew the wrong dragons. Additionally, a very big thank you goes to him for his courage to be my initial and on-going editor. Because of him it was not such a long strange trip after all.

I am grateful to my parents for their work ethic that lives on in me. I learned to love working the quiet pre-dawn hours and came to re-realize just how bright the stars shine at 3:30 am. Thank you to my sister too: Jeanie carried and navigated our family through some difficult times when I could only be a passenger. Also, she knows just when and how to pamper better than anyone!

Thank you to Merlin, my unconditionally loving dog; his dropping toys at my feet was a strong reminder to keep the balance between work and play.

Deep appreciation goes to my step sons, Shiva and Ben, for their love and support. Our treasured get-togethers have been indelibly empowering, reminding me that we—individually and as a family—can do and get through anything.

Last, I would like to thank Alex, my long time friend, philosophy guru, and Tai Chi master. He helped me discover the inner quiet to offset the outer chaos, and did so with the warmest teachings and musings. I wish he were still here so that we could 'push hands' one more time; to feel my focus now and my stronger-than-ever energy. This strength (in my energy) remains humble; it is how I will forever carry Alex in my heart.

I would like to dedicate this paper to my daughters, Chelsea and Cassie, who have many times lent me their childhood spirit and wonder, and provided me with their constant unconditional acceptance. One day they will no long wonder why their mommy roused them out of bed at 4 a.m. to watch a meteor shower, stopped the car abruptly to pick a ripe May apple, or impulsively drove out of the way to see a springtime pasture covered in a flowery purple haze. It was sharing these moments of specialness together that provided me a profound rejuvenating pause. The times I could not feel it or see it from my own eyes I looked to theirs to regain the experiences of unspoiled surprise and joy. It was the little things such as these special moments that renewed my momentum, but it was the big things, like having my girls in my life and with whom to share these moments that provided the deepest sense of meaning, purpose, and direction not only for that path I was taking but in life as a whole.

ABSTRACT

This correlational study investigates the incremental validity of the Reactive (R) composite scale of the Psychological Inventory of Criminal Thinking Styles (PICTS) relative to Psychopathy Checklist: Screening Version (PCL:SV) total score for predicting medium security federal adult male inmate adjustment over a 12 month period. Adjustment, the criterion variable, was operationalized as the number of incident reports received over 12 months. Archival data for 146 offenders were obtained for incident reports and categorized as aggressive or non-aggressive. Scores for the PICTS P and R composite scales were obtained from archival electronic files. Data for rating the PCL:SV were gathered from each inmate's presentencing investigation file. Two statistical models were employed for analyzing the eight hypotheses of this study. The first model included the traditional linear correlation and logistic regression analyses. The second model, which included univariate and multivariate negative binomial regression analyses, was implemented to specifically address the unique qualities of the distribution of the criterion variable. In the preliminary part of this correlational investigation, five demographic variables (age, education level, ethnic status, marital status, type of confining offense) and two psychometric variables and selected subscales (PCL:SV total, Part I and Part II scales and the PICTS P and R scales) were assessed to determine their relationships with the criterion variable. The primary hypothesis investigated incremental validity between the PCL:SV total score and the PICTS R composite scale. The findings using the two statistical models indicated that the logistic regression provided limited findings; however, the negative binomial regression, which in addition to replicating the findings of the logistic regression model, found additional significant findings. The primary hypothesis was partially supported in that significant incremental validity was found for the PCL:SV total score and the PICTS R composite scale for total incident reports, however not beyond age.

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Use your imagination not to scare yourself to death

but to inspire yourself to life.

Adele Brookman (1946-)

CHAPTER 1

INTRODUCTION

Prevalence of Imprisonment

The number of incarcerated individuals in the United States exceeded two million in 2004 according to the Bureau of Justice Statistics (BJS, 2005). That is, 123 females and 1,348 males per 100,000 United States residents were incarcerated (BJS, 2005). If the current rate of incarceration remains constant, 6.6% or 1 in 15 of the United States residents born in 2001 will be imprisoned during their lifetimes (BJS, 2003a). This suggests that among men, 1 in every 3 black males, 1 in every 6 Hispanic males, and 1 in every 17 white males are expected to go to prison during their lifetimes (BJS, 2003b).

The prevalence rate for individuals who were incarcerated for the first time in 2001 was 129 per 100,000 United States residents (BJS, 2003b). The main offenses resulting in incarceration in 2000 were for drugs and violent offenses. An estimated 57% of federal inmates and 21% of state inmates were involved in drug related offenses and about 10% of federal inmates and 49% of state inmates were incarcerated for violent offenses (BJS, 2003a).

The largest age group of imprisoned males is the 35 to 44 year old group (BJS, 2003b). The chance of going to prison for the first time declines with age: at age 20 the chance of a male going to prison is 4.1% for white men and 25.3% for black men (BJS, 1997). By age 30 it is 2.1% and 10.8% respectively. This drop in rates continues, so that by the age of 45 the chance of going to prison is .8% for white men and 2.1% for black men (BJS, 1997).

Correctional Institutions

There are approximately 1,600 adult correctional institutions in operation in the United Sates (BJS, 2003c). These facilities are state, federally, or privately operated, with the bulk of them state operated. In 2000, there were 1,320 state facilities, 264 private facilities, and 84 federal facilities in operation (BJS, 2003c).

An estimated 88% of inmates were under state jurisdiction and 12% under federal jurisdiction in 2004 (BJS, 2005). State crimes are violations of state and local statutes which include drug sales, under the influence, rape, child abuse, and domestic violence. Federal crimes are those defined by the U.S. Constitution or by federal statutes, and include: interstate crimes, internet crimes, large quantity narcotic conspiracy, smuggling controlled substances, bank robbery, bank fraud, and mail fraud.

Through placement procedures individuals who are sentenced to prison are assessed for their criminal propensities, their dangerous proclivities, and their own needs; this is done in order to match them with the appropriate facility and appropriate accommodations within the facility. In this process, offenders are assessed and assigned a security level according to their perceived public safety risks. Nearly 1 in 5 offenders are classified as maximum security risks, 2 in 5 are classified as medium security risks, and 2 in 5 are classified as minimum security risks or as unclassified (BJS, 2003c). In 2003, state facilities contained the largest number of inmates classified as maximum security (21%) and federal facilities had the largest number of inmates classified as minimum security (61%) (BJS 2003c).

Security risk assessments are implemented not only to keep the public safe but also to keep inmates and staff within the confines of the correctional institution safe. In a 12-month period from 1999 to 2000, state and federal facilities reported more than 34,000 inmate-on-inmate assaults resulting in 53 deaths, and 18,000 inmate-on-staff assaults resulting in 5 deaths (BJS, 3003d).

The experience of imprisonment is a concern for psychologists and criminologists who search for ways to forecast which inmates will experience the greatest difficulty adjusting to prison. Predicting behavior such as misconduct has great appeal but it has proven to be a formidable task.

Statement of the Problem

Misconduct occurs in all correctional institutions, but it is the aggressive and assaultive infractions that are of prime concern for prison administrators (Cullen, Latessa, Burton, & Lombardo, 1993). The large number of assaults and deaths that occur in institutions has been the impetus for the research community to find ways to reduce these statistics and to increase personal safety for the staff, other inmates, the individual, and the outside community. In addition to human damage, there is often property damage, staff distress, and inmate lawsuits, at a cost to the prison system of over $9 million annually (Lovell & Jemelka, 1996). Thus, early identification of inmates at risk for aggressive misconduct could circumvent the detrimental effects of maladjusted offenders, reduce overall costs, and provide direction for more efficient distribution of resources to prospective institutional treatment programs.

The impact of misconduct in correctional institutions has produced a strong need for assessing risk and maladjustment. Research continues to search for strong and consistent correlates of maladjustment in order to predict accurately and to prevent misconduct, particularly aggressive types of misconduct. There are a number of risk assessment instruments currently available, as well as new ones being developed; there are also ones that have already been developed and are being improved upon. Two psychometric instruments, the Psychological Inventory of Criminal Thinking Styles Version 4.0 (PICTS; Walters, 2001a) and the Psychopathy Checklist: Screening Version (PCL: SV; Hart, Cox, & Hare, 1995), have individually demonstrated moderate to good predictive ability for forecasting institutional maladjustment (Monahan et al., 2001; Walters, 2002). A search of the literature indicates that these two psychometric tests have not been combined in part or in whole for investigating increased predictive accuracy. The present study seeks to determine if combining the PICTS Reactive scale relative to the PCL:SV total score will demonstrate significantly greater ability for predicting institutional adjustment.

Purpose of the Study

The purpose of this study was to explore the incremental validity of two psychometric instruments for predicting prison adjustment among adult males, using incident reports as an index of adjustment. The first psychometric, the PCL:SV is based on the personality construct of psychopathy, which encompasses interpersonal, affective, and behavioral features associated with a socially deviant lifestyle (Hare, 1991). The PCL:SV includes a semi-structured interview and a 12-item symptom rating scale that has correlated with adjustment to prison (Hill, Rogers, & Bickford, 1996). In the present study the PCL: SV total score was the psychometric variable of interest from the PCL: SV. The PCL: SV scores were derived from paper presentencing investigation files.

The second psychometric, the PICTS, is an 80-item self-report instrument that measures eight thinking styles which are thought to maintain a criminal lifestyle. Two scales on the PICTS derived from these eight thinking styles are the Reactive (R) scale and the Proactive (P) composite scales. These two composite scales have been found to be more effective than individual thinking style scales in predicting institutional adjustment (Walters, in press a). The PICTS R scale measures reactive or retaliatory criminal ideation and the PICTS P scale measures proactive or instrumental criminal ideation. The R scale has shown a stronger and more consistent correlation with disciplinary reports than the P scale (Walters & Geyer, 2005) and therefore the R scale was selected as a psychometric measurement from the PICTS. Participants were administered the PICTS upon admission to the correctional institution as part of the routine entrance procedure, and their performance scores were collected from archived electronic files at the facility.

Institutional adjustment was operationalized as the number of incident reports received by an inmate over a 12 month period. Incident reports were inspected both for total number of incident reports and types of incident report (aggressive versus non-aggressive). Incident report data were acquired from electronic records maintained by the Federal Bureau of Prisons.

Data used in this study were retrieved from archival sources and analyzed by correlational methods. The preliminary statistical analyses in this study examined the relationships between certain demographics (age, education level, ethnic status, marital status, and confining offense) and the criterion variable (incident reports). Those demographics showing significant relationships with the criterion variable were carried over to the subsequent primary regression analyses for further investigation as control variables.

After the preliminary statistical analyses, a second set of analyses were conducted to explore the relationship between the psychometric predictor variables (PCL:SV and PICTS) and the criterion variable, incident reports. The final and the primary statistical investigation consisted of regressions performed on the predictor variables and control variables to explore incremental validity in predicting adjustment (operationalized as the number of incident reports).

Two statistical models were employed for analyzing the primary regression analyses: The logistic regression analysis model was used to analyze the data when the criterion variable was represented as dichotomized data and the negative binomial regression model was used to analyze the data when the criterion variable was represented as count data. Thus, there were 36 analyses conducted; they were conducted representing the criterion variable as dichotomized data initially and then re-analyzed representing the criterion variable as count data.

CHAPTER 2

LITERATURE REVIEW

The Experience of Imprisonment

Prison experience involves the involuntary removal of an individual from family, friends, and a familiar life style and his or her placement into an environment defined by confinement, fewer resources, more constraints, and regimented routine. Prison is a forced inclusion to a closed, single-sex social milieu replete with a subculture that has its own set of unique roles, norms, attitudes, and language. Incarcerated individuals find it especially difficult at the beginning of their sentences as they adjust to this new subculture (MacKenzie & Goodstein, 1985; Toch, Adams, & Grant, 1989; Wright, 1991a). After the initial discomfort, emotional state, health, and conduct generally tend to improve (Toch, et al., 1989; Coughlin, 1995).

Zamble and Porporino (1988) noted that newly admitted inmates primarily had the greatest difficulty with deprivation from their families and friends (82%), loss of freedom (44%), not having the ability to acquire preferred items, and an inability to participate in activities of their choices (35%). After a few weeks post incarceration, inmates tended to acclimate to the loss of freedom, focusing less on the overriding losses of their “old” lives and more on the concerns involving daily events. For instance, inmates missed being able to lie in the sun on a clear day or being able to use their favorite shampoo (Zamble & Porporino, 1988).

It has been suggested that inmates suffer negative consequences from imprisonment (Clemmer, 1940). These negative consequences included stress, violence, depression, illness, psychiatric commitments, and suicide. Other criminal researchers failed to substantiate these outcomes and, in fact, a few studies have contradicted these findings, indicating inmates were unaffected or showed some improvement during the course of imprisonment (Bukstel & Kilmann, 1980; Zamble & Porporino, 1988). It was proposed that prison plays a role in reducing stress in at least two ways. First, because the number of daily personal decisions is reduced, the related stress and pressure are reduced; and second, prison offers external control that helps prevent individuals from acting in ways that might otherwise have deleterious consequences (Bonta & Gendreau, 1990; Zamble, 1992; Zamble & Porporino, 1988).

Nonetheless incarceration tends to be a challenging experience, particularly at the commencement of a sentence. A new incarcerate will require time to acclimate, adapt, and learn behaviors that are in accordance with rules, regulations, and restrictions imposed by the institution as well as by sanctions imposed by other inmates. The latter includes a prison subculture existing separate from, but within the larger prison culture. This inmate sub-subculture has been described as an informal social system with its own norms and values (Ireland, 2002). This system has mores referred to as the ‘inmate code,’ to which all prisoners are expected to adhere. Examples of the inmate code include not fraternizing with staff and not informing (“snitching”) on other inmates (Ireland, 2002).

Not every inmate successfully adjusts to prison. Those struggling will typically exhibit behaviors indicating maladjustment. Signs of maladaption include the inability to accomplish goals (e.g., not completing programs while in prison), creating problems for the environment (e.g., aggressing towards self or others), and an inability to negotiate the environment (e.g., reoffending) (Motiuk, & Blanchette, 2001; Ogloff, Wong, & Greenwood, 1990; Toch & Adams, 2002; Toch, et al., 1989; Walters, 1992; Walters & Geyer, 2005; Zamble & Porporino, 1990). Maladjusted inmates also tend to have difficulty following prison rules and as a result will commit more infractions, receiving more incident reports than adjusted inmates (Toch et al., 1989).

Incident reports, which are also called disciplinary reports, are records of an inmate's misconduct while in prison. Disciplinary reports have traditionally been viewed as a measure of adjustment (or maladjustment) while incarcerated (Wolf, Frienek, & Schaffer, 1966). They also have significance for legal decisions (bail, sentencing, and release), for providing security ratings, and for recommendations to treatment programs.

Disciplinary Infractions

Maintaining safety in prisons is a critical concern for management and staff (Cullen, et al., 1993). Misconduct occurs in all prisons, but it is the more serious infractions involving aggression that are of primary concern. Misconduct can be categorized as violent or nonviolent and can be described by frequency and severity

(Myers & Levy, 1978). Violent or aggressive disciplinary infractions include incidents such as physical assaults (on others, self, or objects), fighting, and threatening. Nonviolent, or non-aggressive, infractions include incidents such as disobeying an officer, refusing to work, and possessing contraband. When these infractions occur and are observed by the staff they are documented as disciplinary reports. These discipline reports tally the cumulative frequency and degree of severity of each incident for the entire sentence the inmate serves.

A number of researchers regard disciplinary reports as reliable and valid measures of conduct and adjustment. Disciplinary records are considered reliable because they represent an exhaustively maintained inventory of judgment that has been spread across many staff members, and because they are operationalized by prison codebooks (Toch, et al., 1989). The validity of disciplinary reports receives support because institutional incidents, particularly serious infractions, are often highly visible (Toch, et al., 1989).

Some criminologists, however, view the reliability of disciplinary reports with less enthusiasm. Concerns include the subjective discretion of those notating infractions and the inconsistent enforcement of prison policy by all staff (Light, 1990; Poole & Regoli, 1980). The potential for not detecting clandestine incidents has also been a criticism; for example, sexual offenses in particular are believed to be less obvious and underreported (Lockwood, 1980). Nevertheless, despite the flaws, disciplinary reports are widely used because they are easily accessible and provide a wealth of information about behavior in the prison setting.

Correlates of Misconduct

For decades researchers have sought the variables associated with misconduct. It was thought that by knowing these correlates, predicting maladjusted behavior would become a less nettlesome task. Numerous variables related to misconduct have been studied, ranging from broad generalizations to more detailed particulars. Broader generalizations commonly studied include timing of infractions during prison terms and trends in the occurrence of incident reports; detailed particulars commonly studied include situational and personal variables which are further divided into more specific factors.

Timing of Infractions

The beginning of a prison term is the period during which incidents are most likely to occur (Cao, Zhao, & Van Dine, 1997; Toch et al., 1989; Wright, 1991a). Toch et al. (1989) discovered that incident reports peaked between 6 to 9 months after admission, and were lowest at the end of a prison term regardless of sentence length. They discovered a characteristic sharp rise and a subsequent fall in disciplinary rates, describing it as a “transition shock” and noting it occurs with the initial adjustment. Thus, the transition to prison life is characterized by the highest levels of nonconformity (Toch et al., 1989; Wright, 1991a).

Incident Report Tendencies

In studying more than 10,000 inmates in the New York State prisons, Toch et al. (1989) found the average disciplinary rate to be 3.6 infractions per year per inmate. Other studies indicated similar mean rates (Walters, 1996; Edens, Poythress, & Lilienfeld, 1999). To better understand incident reports, authors have studied the most common types of infractions, inmates responsible for the greatest number of offenses, rates of misconduct, timing of the first incident report, and infraction specialization.

Common Types of Infractions

The first type of infraction that inmates receive is usually for disobeying an order (Craddock, 1996). Not only is disobeying an order the first one, but is also the most prevalent infraction overall (Craddock, 1996; DeLisi, 2003; Geissler, 1988; Toch, et al., 1989). The second most common type of infraction is failure to follow facility rules or refusing to work. Other frequent charges are related to inmate movement (specific times when inmates are permitted to move in the compound) and to interference with or harassment of staff (Craddock, 1996; Toch, et al., 1989).

Offending Inmates

It appears that most inmates never commit serious infractions. For example, DeLisi (2003) found that 74% (N = 1,005) of inmates from the southwestern United

States never received a serious violation.

However, a small proportion of inmates seem to be responsible for receiving a large number of disciplinary infractions (Acevedo & Bakken, 2003; DeLisi, 2003; Lindquist, 1980; Toch et al, 1989). For example, 5% of the total prison population in one study (Lindquist, 1980) accounted for over half of the violations. In another study, Craddock (1996) reviewed data from 3,551 inmates at the North Carolina Division of Prisons, finding that approximately 10% of the male inmates had received 15 or more incident reports over five years (Craddock, 1996).

Similarly, DeLisi (2001) found that fewer than 8% of the inmates committed over 30 crimes and violations while incarcerated over an average of five years. Of those who were charged with serious offenses in this study, 14% received incident reports for simple assault, 12.5% for threatening staff and about 12% for weapon possession. Prevalence rates were lower for aggravated assault, rioting, arson, extortion, escape, rape, homicide, and hostage taking (DeLisi, 2003). It was a small group (8%) that accounted for 100% of the homicides, 75% of the rapes, 80% of the arsons, and 50% of the aggravated assaults (DeLisi, 2001).

Criminal scientists have concluded that in any offender population a relatively small cluster of individuals are responsible for committing the majority of serious offenses. Inmates who engaged in disturbingly high levels of misconduct and violations while in prison have been referred to as career offenders or as the “violent few” (DeLisi, 2001). It was suggested that instead of using incarceration as “downtime” from offending, these “violent few” continue to engage in offending (DeLisi, 2003).

Rates of Misconduct and Timing of the First Incident Report

Rates of misconduct are correlated with the length of time between entering prison and committing the first infraction. When there is a delay in time between entering prison and commission of the first infraction, overall infractions rates tend to be minimal (Camp, Gaes, Langan, & Saylor, 2003). When there is less delay between the start of incarceration and commission of the first infraction, the rate of misconduct tends to be higher. That is, inmates with longer periods without incident reports were less likely to commit infractions (Camp, et al., 2003; Cradock, 1996). However, inmates who committed violations within 30 days of incarceration had a rate of infractions that was 4 times greater than inmates who committed violations at 150 days (Toch et al., 1989). An additional finding is that men in maximum/close custody begin to violate rules sooner and incur more incident reports than offenders in lower level custody facilities (Craddock, 1996).

Infraction Specialization

It has been noted that there may be some consistency, or “specialization” in the type of infractions committed by inmates (Craddock, 1996). Inmates with multiple successive infractions tended to commit the same type of infractions as the initial infraction. This was true especially for drug and alcohol related incidents (Craddock, 1996; Toch, et al., 1989).

Situational Variables

More specific factors investigated as covariates of misconduct included a number of situational variables. Situational variables are events or imposed environmental factors that impact inmates' behaviors. In the prison setting a number of situational variables have been studied; these include crowding, the offender's previous contact with the criminal justice system, length of the inmate's prison sentence, and the type of confining offense for which the inmate was imprisoned.

Crowding

The research on crowding and misconduct fails to reveal consistent directional correlations with prison infractions. Studies offer evidence for positive correlations (Nacci, Teitelbaum, & Prather, 1977), no relationship (Bonta & Nanckivell, 1980; Camp, et al., 2003), and negative correlations (Walters, 1998) between crowding and disciplinary infractions. In tying to make sense of this, several authors suggested that it is a variety of complex factors related to crowding that affects misconduct: inmate turnover, type of inmate, program availability, and management style (Bonta & Gendreau, 1990; DeLisi, 2003; Eckland-Olson, Barrick, & Cohen, 1983; Gaes 1994; Ruback & Carr, 1993; Walters, 1998).

Previous Contact with the Criminal Justice System

Findings from a number of studies suggest that as the number of prior incarcerations increased so did misconduct (Camp, et al., 2003; DeLisi, 2003; Faily & Roundtree, 1979; Goetting & Howsen, 1986; Hare, Clark, Grann, & Thornoton, 2000; Zamble & Porporino, 1988). Yet, other studies found that individuals with a history of prior incarceration posed fewer problems compared with inmates having no prior experience in prison (Clemmer, 1940; Craddock, 1996; Wolfgang, 1961). Craddock (1996) was more specific, finding that men both with prior incarcerations and experience in juvenile training school had 23% less likelihood of receiving infractions compared with men who had neither experience. It was suggested that these men learned to cope in prison without violating the rules or that they learned how to avoid detection.

Length of Prison Sentence

It appears that infraction rates are generally negatively correlated with length of sentence. Inmates with shorter sentences were found to have a higher rate of infractions than inmates with longer terms (Faily & Rountree 1979, Flanagan, 1980; Lindquist, 1980). In one study, the mean infraction rate for inmates serving short terms was double the mean of infraction rates for inmates serving long term sentences (Flanagan, 1980). In another study infraction rates did not vary much across time-served groups with the exception of long-term inmates, who had a substantially lower average annual rate (2.6) than the other inmates (3.6) (Toch & Adams, 2002).

It is suggested that those inmates incarcerated longer may not want to risk losing earned privileges, that they may have learned to avoid detection, or that the increasing familiarity between corrections officers and inmates leads to more lax surveillance of inmates (Toch, et al., 1989; Wright, 1991a; Zamble, 1992).

Type of Confining Offense

Last of the situational variables suspected of covarying with adjustment is confining offense. Confining offense refers to the type of offense for which an offender was incarcerated. Studies on confining offense and frequency of incident reports produced mixed results. In a number of studies, inmates who committed violent crimes received more aggressive incident reports than inmates who were incarcerated for non-aggressive offenses (Finn, 1995; Wooldredge, 1991). Others found that type of offense was significant; however, it was shown to be a weak predictor of infraction rates, increasing the amount of explained variance by approximately 1% in their studies (Toch & Adams, 2002).

In contrast to these studies, other criminologists indicated that there is either no correlation or even an inverse relationship between confining offense and aggressive incident reports. Finn (1995) found no significance in the relationship between prior violence (as measured by prior arrests for violent crime or current conviction for a violent crime) and violent disciplinary incidents. In fact, Toch and Adams (2002) discovered that individuals convicted of murder, rape, assault, and drug offenses had lower infraction rates, when compared with those, for example, convicted of burglary.

Personal Variables

Factors specifically related to the individual (versus the environment) are regarded as personal variables. Over the last several decades, a large number of personal variables have been studied as possible links to predicting disciplinary infractions. It appears that the more common variables studied or the variables increasing in importance with regard to inmate adjustment include age, marital status, education level, ethnic status, psychopathy, and cognitions.

Age

Age seems to be the most robust predictor of adjustment. As age increases (after 25 years), the frequency and severity of disciplinary infractions decrease (Camp, et al., 2003; Craddock, 1996; Faily & Roundtree, 1979; Flanagan, 1983; Goetting & Howsen, 1986; Toch et al., 1989). Further, the age of an inmate at admission to prison is inversely related to the likelihood of misconduct (Finn, 1995; Flanagan, 1980; MacKenzie, 1987; Porporino & Zamble, 1984; Toch, et al., 1989). Younger inmates were found to be involved in more disciplinary infractions (Porporino & Zamble, 1984), inmate-inmate assaults (Ekland-Olson, et al., 1983), and inmate-staff assaults (Wright, 1991b). It has been suggested that the costs and consequences of aggression, including the likelihood of punishment are learned through the process of aging (Wilson & Hernstein, 1986).

Marital Status and Level of Education

Married inmates and inmates with at least high school diplomas were less likely to be involved in disciplinary infractions (Faily & Roundtree, 1979; Finn, 1995; Flanagan, 1983; MacKenzie, 1987; Myers & Levy, 1978; Toch et al., 1989; Wooldredge, 1991). It is suggested that as individuals age, they engage in social commitments such as marriage and careers and consequently become more prosocial (Greenberg, 1985).

Ethnic Status

Ethnic status seems to be associated with prison adjustment, although the findings are mixed (e.g., Craddock, 1996; Poole & Regoli, 1980; Toch et al., 1989). Overall, evidence suggests that black inmates receive significantly more disciplinary reports than white inmates (Flanagan, 1983; Lindquist, 1980; Poole & Regoli, 1980; Van Voorhis, 1993). However, it has been suggested that caution needs to be exercised when interpreting data on race and infraction rates. The issue is whether or not Blacks actually commit more infractions or that correctional workers are more apt to write up black than white inmates (Hewitt, Poole, & Regoli, 1984).

Psychopathy

The construct of psychopathy is a personality style characterized by affective and behavioral elements. The affective component, which also encompasses interpersonal style, includes characteristics such as glibness, grandiosity, lack of remorse, lying, callousness, and shallow affect. The behavioral component includes characteristics such as antisocial actions, impulsivity, and irresponsibility (Hare, 1991). Elevated scores on tests of psychopathy have been associated with incidents both of verbal and of physical aggression, more segregation time, and have been predictive of institutional violence (Hart, 1998; Heilbrun, et al., 1998; Hildebrand, de Ruiter, & Nijman, 2004; Monahan, et al., 2001). Although psychopathy is related to physical aggression, the physical aggression tends to be other-directed. In one study 35% of the physical aggression by nonpsychopaths was self-directed (suicide attempts and self-mutilation), yet none of the physical aggression by psychopaths was self-directed (Hill, et al., 1996).

Cognitions

It has been suggested that maladjusted behavior is supported by thoughts, or cognitions, that are erroneous (Walters, 1990; Yochelson & Samenow, 1976). Cognitions refer to the automatic processes of the cognitive system; under normal circumstances these are not in conscious awareness. These include processes, including how an individual receives information from the environment, how an individual decides whether or not a situation is personally threatening, how an individual retrieves information, or how an individual recalls events. Although these events occur rapidly and out of awareness they play a large part in mediating emotions and behavior (Beck & Clark, 1988).

Philosophers as far back as the Greek and Roman times have highlighted the role of cognitive factors. For example, Epictetus stated, “Men are disturbed not by events, but by the views they take of them.” Similarly, in presenting a theory of criminal behavior, Walters and White (1989) discuss a number of developmental variables that contribute to chronic reoffending and conclude, “Regardless of which factors are involved, it is the offender’s beliefs about these developmental experiences, not the experiences themselves, which serve as the foundation for later lawbreaking behavior” (p. 2).

The integral role that cognitions play in mediating emotional and behavioral responses was advanced in the Twentieth Century by Albert Ellis (1962) and Aaron Beck (1963), the developers of Rational Emotive Therapy and Cognitive Therapy, respectively. Both therapies suggested that the problems people face often stem from core beliefs that are illogical or irrational. These erroneous core beliefs, stemming from schemas, affect the person’s view of the world, and consequently lead to dysfunctional emotions and behavior.

Schemas are operationally defined as situations in which information received by an individual is guided and given meaning. In cognitive theory, Beck and Emery (1979) theorized that schemas attach meaning and make sense of incoming information by organizing it to fit personalized preconceived notions. Schemas can be organized and given meaning to the point where “ideational themes” can dominate and further determine the manner in which incoming information is processed (Beck, 1976).

Schemas develop early in life, become reinforced over time, and become consolidated by young adulthood (Guidano & Liotti, 1985; Young, 1990). Schemas are adaptive but they can also be maladaptive when they lead to errors in thinking and when, subsequently, they lead to dysfunctional behavior. There seems to be a relationship between cognitive content (what a person is thinking), the cognitive process (how the individual uses the information), and the occurrence of the specific symptoms or behaviors (Freeman & Reinecke, 1995). Cognitive theory proposes that dysfunctional feelings and conduct are largely due to the function of schemas (Beck, 1964; Freeman, Pretzer, Fleming, & Simon, 1990). For example, schemas can oversensitize individuals to hostile intention in others and therefore these individuals learn to respond aggressively to their perceptions of hostility from others (Serin & Kuriychuck, 1994). Moreover, cognitive processes were shown to have an impact on inmates' adjustments to prison. Inmates with the greatest number of adjustment problems demonstrated more irrational thinking than inmates with fewer adjustment problems (Evans & Picano, 1984).

Cognitive errors and offending. Yochelson and Samenow (1976) used the idea of cognitive errors and applied it to the offender population. From case study reviews, Yochelson and Samenow generated a list of 52 thinking errors fundamental to criminal behavior. They described the main cognitive distortions which the offenders used as the over-valuing of self-centered attitudes and thoughts that entitle an individual to behave in an antisocial manner. Although Yochelson and Samenow's work was criticized for being difficult to evaluate empirically (Hagan, 1986), it was an inspiration to other researchers. Psychologists at the U.S Penitentiary in Leavenworth, Kansas developed a system of criminal ideation that included eight primary cognitive errors, five of which were originally named by Yochelson and Samenow (Walters & White, 1989). According to Walters (1990) a primary tenet of the chronic criminal behavior, also known as a criminal lifestyle, is that cognitions, motives, and actions are meaningfully connected.

Examples of distorted thoughts that criminals may experience include: “If I’m not in control it means I’m weak;” “When the pressure gets too much, I say ‘the hell with it;’” “When it’s all done and said, society owes me;” and “He (the victim) deserved what he got” (Walters, 1990; Walters & White, 1989). Established clusters of these thinking errors have been able to predict disciplinary infractions in male offenders (Walters, 1996; 2005a).

Summary

It appears there is a period of adjustment over the first year of imprisonment. The difficulty of transition is reflected in infraction rates, which have been found to be highest in the first 6 to 9 months of incarceration (Toch, et al., 1989). The majority of inmates do not receive incident reports. Yet there tends to be a small number of inmates who commit a large number of aggressive incidents and who are considered the “violent few” (DeLisi, 2001). Through decades of research investigators have sought variables that could predict those inmates who will be maladjusted. Some correlates linked to prison adjustment are clear and consistent and others are equivocal and perhaps tied to more complex considerations. The more commonly researched correlates include age, ethnic status, education level, marital status, and confining offense. These particular demographics were incorporated into the present study. With the exception of ethnic status these variables have shown a relatively clear relationship with infraction rates. Ethnic status is included in the present study to provide clarifying information as a correlate of disciplinary infractions. The personal variables of psychopathic characteristics and cognitions are variables connected to maladjustment and are included as integral elements in the primary investigation of the present study.

Predicting Behavior

The primary goal of predicting behavior is to make an accurate statement about future events before they occur. Risk assessments are used as a means for making predictions or estimates about the level of risk an individual presents for certain types of dangerous behavior. The salient issue in predicting behavior is the accuracy between the prediction and that which actually occurs.

Making a prediction about behavior typically begins with an assessment. Assessments are based on a variety of test scores from multiple test methods, from referral information, and from observation; these are considered in the context of the individual's history in order to understand the person being evaluated.

Predicting behavior such as inmate adjustment, for example, has great appeal because of the numerous benefits it could potentially provide. However, predicting behavior, such as aggression, has a history of doubters (e.g., Monahan, 1981). The long-held doubts that shadowed the earlier research community has lessened somewhat as a result of more recent risk assessments which were better conceptualized, and more reliably scored. Additionally, these newer assessments have demonstrated moderate predictive validity, and have shown superiority over unaided clinical judgment in predictive ability (Doyle, Dolan, & McGovern, 2002; Heilbrun, O'Neill, Strohman, Bowman, & Philipson, 2000; Monahan et al., 2001; Quinsey, Harris, Rice, & Cormier, 1998).

Clinicians faced with making a decision about the threat posed by a particular inmate are often expected to provide a definitive yes or no answer because the decision will then lead to taking or not taking certain subsequent actions. Ideally, institutional risk assessment is the ability to forecast aggressive or socially disruptive behavior before it occurs. Realistically, institutional risk assessment is an *estimate of likelihood* that institutional misconduct will occur (Hart, 1998). Providing a dichotomous yes-no answer for forecasting aggressive behavior presents a difficult challenge because accuracy in decision-making is affected by a number of other factors. These factors include reliability of measurements, base rates, and selection ratios.

Predictive Accuracy

Predictions of risk in a correctional institution are of critical importance, yet they are helpful only if they are consistent and accurate. A 2 x 2 prediction table is a way to represent and assess the possible outcomes of predictions.

2 x 2

The 2 x 2 prediction accuracy table consists of four cells that represent the possible outcomes resulting from predictions: two predictions of behavior (e.g., it will occur versus it will not occur) and two types of resulting behavior (e.g., it did occur versus it did not occur). The two predictions and the two types of resulting behavior produce four outcomes: two correct predictions and two incorrect predictions. The correct predictions indicate: the behavior was predicted and it occurred, called a true positive; and the behavior was predicted not to occur and it did not occur, called a true negative. The two incorrect predictions are: the behavior was predicted to occur but it did not occur, called a false positive; and the behavior was predicted not to occur but it occurred, called a false negative. In using these four outcomes, an assessment of predictive accuracy can be calculated.

Factors Affecting Predictive Accuracy

Offenders are commonly divided, or classified, into groups for decision-making purposes. Inmates may be classified into categories based, for example, on intelligence, prior work history, or offense behavior; from these classifications decisions and predictions can be made. The means by which inmates are initially assigned to classification groups is usually through some type of assessment.

Assessments are often used with the intention of classifying and predicting some outcome; thus they are termed predictor variables. Particular attention needs to be paid to the importance of the factors that affect the ability of these predictor variables to make accurate prognostications. Accuracy in prediction can be enhanced by awareness of the following important factors: reliability, base rates, and selection ratios.

Reliability

Reliability is an indicator of a measurement's consistency from one administration to the next. If a test taker scored above the threshold on the first administration of a particular test, but scored below the threshold on the retest, provided everything else remained constant, the instrument has not demonstrated reliability. However, if the same test taker scored both times above (or below) the threshold, reliability is indicated if all else remained constant. Without this type of stability the measure will have poor predictive accuracy.

The same is true for the outcome measure, or criterion variable. For example, if the criterion variable was the number and type of infractions received in a prison setting, but something changed in the way infractions were measured at some point in time, then the reliability of the measure as well as the accuracy of the prediction could be seriously compromised. Thus, the reliability both of the predictor and criterion variables are essential and must not be overlooked (Gottfredson, 1987).

Base Rates

Another factor important for accurate decision making is base rates. Base rates represent the frequency of some characteristic or event occurring in the population of interest. For example, if an event occurred 95 out of 100 times, the base rate would be 95%. With this base rate of 95%, the best strategy for prognostication would be to predict that it will occur because the prediction would be right 95 out of 100 times. If an event occurred 5 out of 100 times it would have a base rate of 5%. The prediction of this event would be much more difficult so it would be wise simply to predict that the event would *not* occur. However, when the consequences of an infrequently occurring event are severe, devising strategies to predict the event, despite the odds, gains importance. Even so, it would require a very potent predictor to outdo the 95% chance that it would not occur.

Forecasting an event that has low rates of occurrence such as prison misconduct presents a difficult challenge. In one study, for example, the base rate of aggressive infractions for prison inmates was 23% (Walters, Duncan, & Geyer, 2003). This base rate represents the percentage of persons with one or more aggressive infractions; 23% of the participants had one or more aggressive infractions and 77% of the sample had no aggressive infractions. To predict that there would be no aggressive misconduct among this sample would be correct 77% of the time. Predicting that there would be misconduct would produce a success rate of 23% --much more difficult due to the low rate of occurrence. Thus, the difficulty in predicting low occurring behavior is indicated in the base rates, the rate of occurrence. Gottfredson (1987) pointed out that some instruments have been developed without consideration for base rates and as a result are actually less accurate than the exclusive use of the base rates for prediction.

Selection Ratios

Typically, instruments developed for assessing behavior have a predetermined decision point in the scoring which serves to separate test takers into groups. These arbitrary or empirically based decision points, called cutting scores, separate the scores of individuals who indicate a condition versus those individuals who do not. For example, a cutting score may separate those offenders expected to have poor adjustment from those who are expected to have good adjustment to prison. The proportion of individuals who qualify as belonging to a designated group or condition as a result of the divisions made by the cutting score is called the selection ratio. If offenders who were expected to have poor adjustment were the condition of interest, the selection ratio would be the proportion of offenders predicted to have poor adjustment in prison.

A property of the selection ratio is that it is subject to change if the cutting score is changed. A changing cutting score not only alters the decision points and the selection ratios, but it also changes the errors made in prediction. Circumstances could arise in which some inmates who scored below the cutting score on a risk assessment, suggesting they are not at risk for misconduct, subsequently engaged in aggressive misconduct. In this case, where the findings counter the prediction, the evaluator may choose to modify the cutting score to avoid such misses in the future. However, there are consequences from modifying the cutting score. In this example if the cutting score were changed in order to reduce the errors called false negatives, there would be an increase in correctly identified inmates (called hits), but there would also be an increase in the number of inmates identified as being at risk but who do not exhibit misconduct (called a false positive or false alarm). Thus, as the number of misses is reduced, the number of false alarms is increased. This dilemma regarding the results of changing cutting scores is called the sensitivity-specificity tradeoff (Quinsey et al., 1998). Improving a test's hit rate comes at the expense of a higher false alarm rate. Hence, the cutting score has a powerful influence on the predictive accuracy of an instrument.

Indices of Accuracy

A number of indices can be used to examine an instrument's accuracy of prediction. These indices include sensitivity, specificity, negative predictive power, and positive predictive power.

Sensitivity and Specificity

The performance of a test is commonly expressed in terms of sensitivity and specificity, which are indices of diagnostic accuracy. These concepts were used by Yerushalmy in 1947 in the biomedical field as a means of assessing the rate of "true" or "false" positive or negative results in x-ray readings. Sensitivity is the proportion of true positives and specificity is the proportion of true negatives. A true positive occurs when the test identifies a case that meets criteria and the expected, associated outcome occurs (e.g., the individual exhibited the predicted aggressive behavior as predicted). A true negative occurs when the test identifies a case that does not meet criteria and the outcome does not occur (e.g., the individual did not meet criteria and had no aggressive behavior). In the present study, sensitivity denotes the proportion of inmates designated as being at risk for aggression and who, in fact, receive disciplinary reports. Specificity represents the proportion of inmates designated as not being at risk and who do not receive incident reports. When it is important not to miss a particular condition, a test with high sensitivity is selected. When it is more critical not to create false positives, because of the serious or costly consequences that might result, clinicians might select an instrument with a higher specificity rating, even though there may be a trade off in the test with lower sensitivity. The ideal test would be both highly sensitive and highly specific.

Positive Predictive Power and Negative Predictive Power

Two other statistics associated with accuracy are derived from sensitivity and specificity. They are called positive predictive power and negative predictive power. These terms represent measures of the predictive utility of a test. Positive predictive power asks, given the base rate, how useful is the test in identifying true positives? Negative predictive power asks, given the base rate, how useful is the test in identifying true negatives? The positive predictive power is the ratio of true-positive results to all positive results, and the negative predictive power is the ratio of true-negative results to all negative results (Griner, Mayewski, Mushlin, & Greenland, 1981). Positive predictive power is high when the specificity is high (and the rate of false positives is low) and negative predictive power is highest when sensitivity is high (and rate of false negatives is low). In contrast to sensitivity and specificity which remain constant within the population being tested, the predictive values of a test depend not only on the sensitivity and specificity of the test but also on the prevalence (base rate) of the condition within the population being tested (Baldessarini, Finkelstein, & Arana, 1983). Therefore when something like aggression is being measured, the significance of positive (or negative) results of a test may be different in a prison setting than in the general public.

Reducing Errors

There are ways to reduce errors in making predictions. First, developing a more accurate test will enhance the effect size. A larger effect size is a stronger indicator of the presence of an event in a population (Quinsey, et al., 1998). Second, allowing for a longer follow up period will produce larger base rates. Extended time allows for the collection of more data, resulting in a larger overall sample of the event. Additionally, samples that are representative of the population, through random sampling, enhance the accuracy of prediction and increases the generalizability of the findings. Although there are a number of methodological strategies for reducing errors, limitations to predictive accuracy still remain.

Limitations arise when predictive accuracies between two measures are compared. If the same cutting point were used by both measures, but one measure used a group that produced a low base rate and a smaller distribution relative to the other measure (assuming the standard deviation is the same for both groups), then hits, misses, false alarms, and true negatives could differ between groups (Quinsey, et al., 1998). Other concerns related to comparing the accuracy of two measures are the similarity or differences in the operational definitions used by each study and the use of higher or lower risk populations by each measure (Quinsey, et al., 1998). To avoid such potential problems an alternate method is available for describing predictive data and for comparing measures. The alternate method for assessing predictive accuracy is called the receiver operating characteristic (ROC) curve analysis.

Assessing Predictive Accuracy

ROC

The ROC curve analysis is a method for evaluating predictive accuracy of a single instrument or for comparing multiple instruments. The important advantage that the ROC analysis offers is that it is not influenced by base rates or by selection ratios. ROCs were originally used for radar signal detection (i.e., deciphering radar signals from noise) and sensory psychology during the 1950s and 1960s (Metz, 1984). Only recently has the ROCs been used for violence risk assessment (Mossman, 1994; Rice & Harris, 1995).

The ROC curve is a graphical plot representing the complete sensitivity and specificity range; graphically, it represents the trade off between false negative and false positive rates for every possible cutting score (versus a single cutting score). On this graph, the Y-axis represents the proportion of true positives (sensitivity) and the X-axis represents the proportion of true negatives (specificity).

Chance is depicted on the ROC graph as a diagonal line drawn from the bottom left abscissa to the top right ordinate in the ROC space. Scores obtained from a given measure will form a curve in relation to this diagonal line. The area between the diagonal line (indicating chance) and the curve (the instrument's performance) is called the area under the curve (AUC). The AUC provides an index of the accuracy of the measure with respect to its ability to predict outcomes. The area can range from 0.0 (perfect negative prediction) to 1.0 (perfect positive prediction). The larger the AUC, the stronger the predictor is for identifying more true positives and fewer false positives. For example, an AUC = .65 means that there is a 65% chance that an individual with a designated condition will score above the cutoff on the predictor variable. An AUC = .50 represents chance prediction. A perfectly accurate test will have a true positive (hit) rate = 1.0 and a false positive (false alarm) rate = 0. The trajectory of this "perfect" curve traces the left hand border of the ROC space and then extends along the top border of the ROC space. A test without predictive accuracy would have an AUC = .5 and would be indicated by a diagonal line in the middle of the ROC space. Such a diagonal line would indicate that the effect size is 0 and that the true positive rate never exceeded the false positive rate (Quinsey, et al., 1998). AUC values of .70 are considered moderate to large, and .75 and above are considered to be large (Webster, Douglas, Eaves, & Hart, 1997).

Data Acquisition for Assessment

Assessing the accuracy of a measurement or prediction is just one step in the process of determining predictive validity. Ensuring predictive accuracy is a critical element that begins at the level of data collection. Data collection requires careful planning and development of methods for the most precise data acquisition.

There are two primary means of collecting data for assessing risk: clinical judgment and actuarial, or evidence based, procedures (Grove & Meehl, 1996; Holt, 1986). Clinical judgment procedures are characterized as informal, subjective, and impressionistic. By contrast, the actuarial, or evidence based procedure is characterized as formal, mechanical, and algorithmic (Grove & Meehl, 1996). In addition to these two methods there are blended approaches, which combine elements from each of these primary methods. Blended approaches include the structured (or guided) clinical assessment and the adjusted actuarial approach.

Clinical Judgment Versus Actuarial or Evidenced Based Method

Clinical judgment is the method traditionally used by mental health clinicians for risk assessments (Grove & Meehl, 1996). Assessments based on clinical judgment are ultimately determined by human judgment (Monahan, 1981). Evaluators gather, review, and integrate information from test data, interview information, and knowledge of the details and characteristics of the case. This information is combined and synthesized to produce an overall impression for making an assessment (Carroll, 1980; Otto, 2000).

A second primary means of collecting data is the actuarial, or evidence based method. These assessments are based on validated relationships between predictor and criterion variables and are ultimately determined by explicit rules (Litwack, 2001). Variables are empirically derived from observation, experimentation, professional ratings or scores from tests, and are operationally defined prior to collecting data (Monahan, 1981; Monahan & Steadman, 1994; Otto, 2000). After these data are collected they are entered into a specified, pre-existing statistical equation (e.g., multiple regression) for calculating the likelihood of behavior (such as misconduct). The rationale for the development and the use of the actuarial method is that it reduces the clinicians' subjective and overall involvement (Otto, 2000). Once a method of statistical prediction is developed, application of mechanical prediction requires no expert judgment and they are 100% reproducible.

Criticisms of Clinical Judgment and Actuarial Methods

Clinical judgment has been accused of having a low accuracy rate as a result of human susceptibility to making specific kinds of errors when processing information (Borum, Otto, & Golding, 1993). Errors in judgment encompass statistical matters such as overlooking base rates, assigning nonoptimal weights to cues, failing to take into account regression toward the mean, failing to assess covariation properly, and low interrater reliability (Gardner, Lidz, Mulvey, & Shaw, 1996; Grove & Meehl, 1996; Quinsey, et al., 1998).

Other errors in clinical judgment are the result of using mental shortcuts called heuristics. Judgment heuristics include strategies such as confirmatory bias (looking for evidence that confirms one's beliefs and ignoring information this is not consistent with those beliefs), illusory correlations (erroneously concluding that there is a relationship between two variables when one does not exist), representativeness (classifying something according to its similarity to a typical case), availability (basing a judgment on the ease with which something can be brought to mind), and affect (assigning "goodness" or "badness" to stimulus words) (Garb, 1998; Kahneman, Slovic, & Tversky, 1982; Slovic, Finucane, Peters, & MacGregor, 2002; Tversky & Kahneman, 1973).

One of the most vigorous areas in clinical decision making in the last 6-7 years has been in the use of evidence-based treatment recommendations (Garb, 2005). This method, too, is not without criticism. Several researchers have identified a number of shortcomings including the following: actuarial data is seductive to the fact finder (i.e., statistical information will assume too much prominence in the fact finder's decision making process); there are many false positive rates ("conviction of innocents"; Monahan, 1981); it is inflexible because it does not consider case specific information; it is not sensitive to changes over time, and it is asserted that population data cannot be applied to individuals (Hart, 1998; Litwack, 2001; Melton, Petrila, Poythress, & Slobogin (1997).

Is One Method Superior?

Many authors suggest the actuarial method is superior to clinical judgment in predicting violence risk (Borum, 1996; Grove & Meehl, 1996; Lidz, Mulvey, & Gardner, 1993). However, it has been pointed out that when policy and decision makers are given a choice between clinical case material and statistical information regarding recidivism, there is a preference for implementing the clinical case material over statistical information (Carroll, 1980).

Regarding accuracy, findings indicate that clinical judgment is twice as likely to be wrong as right when predicting violence (Monahan, 1981). A meta analysis of 136 studies comparing actuarial and clinical approaches in risk prediction found that statistical prediction was superior in up to 47% of the studies and clinical prediction was superior in up to 16% of the cases (Grove, Zald, Lebow, Snitz, & Nelson, 2000). Superiority of the actuarial method was consistent regardless of judgment task, type of judges, judges' experience, or the type of data.

It would appear that both the clinical judgment and actuarial methods have merits, but it is the actuarial method that has not only more supporters, but also empirical evidence corroborating its use in risk assessment and prediction. Some researchers suggest there is sufficient merit to utilize both methods and that by employing a "blended" approach to data collection the benefits of both methods can be reaped (Borum, 2000; Grove & Meehl, 1996; Hanson, 1998; Quinsey, Harris & Rice, 1998).

Blended Approaches

If one were to view the actuarial and clinical risk assessments as two ends of a continuum, the blended methods of risk assessment occupy the intermediary positions.

The first blended approach, the structured or guided clinical assessment method, uses clinical judgment but bases this judgment on structured, empirical risk indicators (Borum, 2000; Hanson, 1998). An example of this blended approach is making decisions by comparing clients with prototypes. The clinician forms impressions of similarities between his or her client and an idealized individual with the prototypical condition or disorder of interest. This approach combines the experience of the seasoned clinician and the use of statistical methods for making decisions. This approach guides clinicians toward pertinent information while gathering data. This is important because studies have shown that clinicians have a tendency not to cover all the key criteria during general assessments (Miller, Dasher, Collins, Griffiths, & Brown, 2001) and that the guided clinical approach has shown better accuracy than the traditional clinical assessment (Borum & Otto, 2000).

The other intermediate point on the hypothetical continuum of risk assessments is the adjusted actuarial approach. This method uses an actuarial formula for making predictions, yet it permits adjustments which might be made using case-specific information not accounted for by the actuarial formula (Grove & Meehl, 1996; Hanson, 1998; Quinsey, Harris & Rice, 1998). It is uncertain if this method is more accurate than pure actuarial predictions (Quinsey et al., 1998). Concerns with the adjusted actuarial approach include contaminating actuarial formulas by making adjustments (Holt, 1986), and the disinclination of more conservative researchers to consider making adjustments to their actuarial risk assessments (Hanson, 1998).

A Note about the Self-Report Format

Risk assessments come in a number of formats, including interview, record review, and self-report. The self-report format warrants a special note because there is a tendency to dismiss it as a means for assessing institutional adjustment. Researches dismiss self-report because offenders are, with justification, seen as deceptive and unreliable respondents (Schretlen & Arkowitz, 1990; Wooldredge, 1991). Further accusations include: (a) inmates distort responses to gain privileges, (b) self-reports have weak content validity, and (c) inmate reading levels are too often below that of the tests (Edens, Hart, Johnson, Johnson, & Olver, 2000). However, in response to these points of concern, Walters (in press b): (a) suggested using validity scales to combat distortions, (b) argued that weak content validity is not relevant for more theoretically informed instruments, and (c) re-examined and brought to light the statistics about literacy among inmates. Literacy statistics indicate that 86% of prisoners have at least an eighth grade reading level (Haiger, Harlow, O'Conner, & Campbell, 1994).

There seems to be a renewed and growing interest in using self-report methods for risk assessment. This coexists with numerous findings that illustrate the effectiveness of self-reports in predicting future behavior. Self-report instruments have shown effectiveness in predicting disciplinary infractions and they have shown equivalent performance or have outperformed interviews, non self-report rating scales, actuarial instruments, and questionnaires (Ahmad & Smith, 1990; Edens, Poythress, & Watkins, 2001; Kroner & Loza, 2001; Wang, et al., 1997; Walters, et al., 2003). For example, a self-report measure, the Personality Assessment Inventory (PAI; Morey, 1991) has been effective in forecasting problematic behavior in forensic (Wang et al., 1997) and correctional populations (Edens, Poythress, et al., 2001; Walters et al., 2003).

Furthermore, other researchers have suggested self-report questionnaires were more valid than individual interviews because there was more information divulged in the questionnaire than there was in the interviews (Ahmed & Smith, 1990).

Walters (in press b) performed a meta-analysis comparing risk-appraisal and self-report in predicting institutional adjustment. Included in this analysis were 22 studies with 27 effect sizes. The self-report measures were mildly superior to risk-assessment strategies in forecasting institutional adjustment. Both self-report and risk-appraisal measures demonstrated incremental validity relative to each other, slightly more than 50% of the time. Two others studies found that risk-appraisal measures demonstrated incremental validity when risk appraisals have not (Walters, et al., 2003; Walters, 2005a). In addition to its empirically demonstrated effectiveness, the obvious advantage for using self-report is the efficiency of time, costs, and personal resources.

Summary

In conclusion, there are a number of ways to acquire data for assessment. Two commonly used methods are clinical judgment and the actuarial method. Intermediary methods exist, which are combinations, or blends, of the clinical judgment and actuarial methods. There are also a number of formats available for assessment purposes. Contrary to prior belief, it appears self-report instruments may be useful for prison populations.

Serin and Brown's (2000) "10 Commandments" of risk assessment provide a final overview and conclusion to assessing risk:

1. Know base rates. Know base rates and the important role they play in predictive accuracy. For example, researchers can expect lower base rates in minimum security facilities compared with maximum security settings.
2. Use multimethod strategies. No single risk assessment instrument can provide accurate predictions for all offenders or all situations (Hart, 1998).
3. Do not confuse shared variance with increased validity. It is important to be aware of the high intercorrelation among risk assessments in order to prevent the belief that they produce increased accuracy (Serin & Amos, 1995).
4. Be wary of clinical overrides. Clinical information can enhance findings of actuarial risk assessments (Hart, 1998), but if clinical information is to be included it needs to be noted and to be kept in check.
5. Heed statistical estimates. Risk appraisals rely on statistical estimates, but it is suggested to leave room for arguable and justifiable revisions.
6. Be aware of the population on which the instrument was normed. The variety of offender populations, demographics, and levels of risk can impact findings and subsequent risk management strategies.

7. Know the limits of the predictions. This commandment suggests clinicians know their findings; know to whom they pertain, the conditions involved, and their reliability.
8. Know false positive and false negative rates for the specific cutoffs. This reflects the concept that different cutting scores yield different types of decision errors.
9. Provide conditional prediction because risk is not static but dynamic (Hart, 1998).
10. Follow an "aide-memoir." An aide-memoir entails collecting information from as many sources as possible to ensure that the clinician has adequate information to complete the appraisal and to decrease errors.

Instruments for Assessing Risk

Clinicians choose assessment instruments and methods based on the clinical setting, referral question, and patient presentation. In a survey of 830 psychologists in state and federal prisons, 65% stated they were involved in assessment procedures of some sort (e.g., personality, intellectual ability, symptom) but that only 13% were involved in risk assessment (Boothby & Clements, 2000).

In correctional settings, referral questions often involve issues of risk assessment and prediction. A number of instruments have gained acceptance for these purposes. These instruments vary according to the type of setting (outpatient, institution, forensic, civil), population (normal, retarded, psychiatric, offenders), and use (predicting violence, recidivism, psychopathy). A discussion of several of the more commonly used risk assessment tools follows.

The first two instruments are the Violence Risk Appraisal Guide (VRAG; Harris, Rice, & Quinsey, 1993) and The Historical, Clinical, Risk-20 (HCR-20; Webster, et al., 1997). These two are similar because both incorporate another instrument, the Psychopathy Checklist-Revised (PCL-R; Hare, 1991) in their assessment instruments. The VRAG was developed to predict recidivism among mentally disordered offenders and is a tool that is based solely on review of personal history. In contrast, the HCR-20 contains personal history as well as clinical and risk management items for assessing recidivism in criminal and psychiatric populations. The twenty items were constructed for a variety of populations, including civil and forensic psychiatric patients and correctional offenders (Webster, et al., 1997).

The Level of Service Inventory-Revised (LSI-R; Andrews & Bonta, 1995) is a theoretically based risk-needs offender assessment that has been used for a wide variety of offender populations and in a variety of settings for predicting violent recidivism (Andrews & Bonta, 1995). The main items on the LSI-R represent the “Big Four” factors associated with recidivism: criminal history, companions, attitudes/orientation, and emotional/personal subcomponents.

The modified Criminal Sentiments Scale (CSS: Shields & Simourd, 1991) is a 41-item, self-report instrument that measures criminal thought content such as attitudes, beliefs, values, and rationalizations that support criminal conduct. Studies on this test suggest that negative attitudes towards the justice system were related to a higher self-identification with other criminals and with future offending (Stevenson, Hall, & Innes, 2003).

Two measures that are successful in forecasting prison adjustment provide the focus of this study; these are the Psychopathy Checklist: Screening Version (PCL: SV; Hart, et al., 1995) and the Psychological Inventory of Criminal Thinking Styles, Version 4.0 (PICTS; Walters, 2001a). The PCL: SV, a risk appraisal procedure rated by clinicians, was developed to identify the construct of psychopathy; the PICTS, a self-report measure administered to inmates, was developed to assess thinking styles that maintain criminal behavior (Walters, 1990). Both of these instruments have been correlated with institutional adjustment (Hare, 1991; Walters, 1996).

The Psychopathy Checklist

Psychopathy

Psychopathy is accepted as a personality disorder by a number of clinicians (e.g., Hart, et al., 1995) even though it is not a diagnostic taxon listed in the Diagnostic and Statistical Manual (*DSM-IV*; American Psychiatric Association, 2000). The construct of psychopathy is mentioned in the *DSM-IV* in the personality disorder section under antisocial personality disorder (ASPD). In this section, terms including sociopathy, dyssocial personality disorder and psychopathy are clustered together along with ASPD, suggesting synonymy. Hare (1993) argued that this clustering of terms blurs important distinctions and stated, “the choice of terms reflects the user’s views on the origins and determinants of the clinical syndrome or disorder” (p 23). The issues for Hare (1993) are how the problem behavior develops and how the pattern and severity of the behavior are manifested. He notes that the term ‘sociopath’ suggests the syndrome stems from social forces (e.g., poor upbringing) whereas the term ‘psychopath’ suggests the syndromes stem from psychological, biological, and genetic factors, in addition to the social factors. Adding to the confusion, the terms psychopath and ASPD are used mistakenly and synonymously by clinicians (Hare, 1993). The confusion is encapsulated in the example in which a single individual can be diagnosed as a sociopath, psychopath, and antisocial by three separate experts.

The confusion between psychopathy and ASPD lies in part in their similarity and overlapping criteria. To differentiate them, psychopathy should be viewed as a more specific diagnosis than ASPD (Hare, 1985). Using an example of individuals who are engaged in criminal behavior will help clarify the distinction between the two constructs: Most criminals will not have the diagnosis of psychopathy but the majority of criminals will have ASPD (Hare, 1993; 2000). Research indicates that the base rates for ASPD among Canadian offenders ranged from 50% to 80% compared with the base rate for psychopathy which was 15% to 30% (Wong, 1988a).

In his landmark book *The Mask of Sanity*, Cleckley (1976) developed the construct of psychopathy by describing the patterns of behavior and personality styles associated with it. Hare (1993) expanded on Cleckley’s work and refined and emphasized the importance of psychopathy as a construct separate from ASPD. The essential difference between ASPD and psychopathy is noted by their defining criteria: ASPD is described in the *DSM-IV* by socially deviant behaviors; and psychopathy is described by Hare (1993) by both socially deviant behaviors and deviant personality traits.

Similar to other personality disorders, psychopathy is defined as occurring early in adolescence (Salekin, Rogers, & Sewell, 1996), being stable across time (Hart & Hare, 1997), and being manifested across a broad range of situations (Hart & Hare, 1997). The socially deviant behaviors for psychopathy are somewhat similar to the criteria listed in the *DSM-IV* for ASPD (failure to conform to social standards, deceitfulness, impulsivity, aggression, disregard for others' safety, irresponsibility, and lack of remorse). The difference, however, is that personality traits are emphasized in defining psychopathy (they are seemingly less important for defining ASPD). The personality traits of a psychopath are a combination of emotional and interpersonal criteria that include glibness, grandiosity, lack of remorse, lack of empathy, deceit, and shallowness of emotions (Hare, 1993). Cooke and Michie (2001) noted that many of the most discriminating features of psychopathy do not play a formal or necessary role in the diagnosis of ASPD.

Hare (1980) created a measure called the Psychopathy Checklist (PCL) to assess the construct of psychopathy. The PCL and its subsequent derivatives, the PCL-R and the PCL: SV are predicated on two primary factors: personality traits and behavioral patterns. These factors are labeled Factor 1 and Factor 2 respectively. Factor 1 personality traits have been described as aggressive narcissism (Meloy, 1992) or callous and remorseless disregard for the rights and feelings of others (Hare, 1991). The personality traits that are associated with Factor 2 include irresponsible, impulsive, thrill-seeking, and antisocial behaviors (Hare, 1991). Researchers have found a weak association between Factor 1 and ASPD but found a strong association between Factor 2 and ASPD diagnosis (Cooke & Michie, 2001).

With few exceptions, many studies support this two-factor model of psychopathy (e.g., Cooke & Michie, 2001; Hobson & Shine, 1998; Harpur, Hare, & Hakstian, 1989; Raine, 1985). However, alternate conceptualizations of the dimensions underlying the PCL have been developed. A three-factor model has been proposed in which Factor 1, personality characteristics, is divided into two factors for a total of three factors (Cooke & Michie, 2001). Another conceptualization is based on hierarchical model that separates the two main factors into two facets each creating a two-factor, four-facet model (Hare, 2003).

Using the Psychopathy Checklist

Use of the PCL-R requires specialized training and supervision (Hare, 1991). The PCL-R is a 20-item symptom rating scale that combines a semi-structured interview with a review of file information for scoring a checklist. The semi-structured interview covers educational history, work history, health history, family history, sexual history, goals, and adolescent and adult impulsive antisocial behavior. File review is used for gathering additional information and for corroborating interview information. Although the sole use of file review is considered non-standard procedure, it may be used when interviews cannot be conducted (Grann, Langstrom, Tengstrom, & Stalenheim, 1998; Hart et al., 1995). An extreme example in which the file-only review is justifiable is in circumstances where consent is not possible as in personality profiling during a hostage or crisis-negotiation (Bodholdt, Richards, & Gacono, 2000).

There is considerable research to indicate that the reliability and validity of a file-only review are sufficient and of high quality (Hare, 2003; Wong, 1988b). Comparing the PCL-R with and without the interview, Hart et al. (1995) observed Factor 1 and Factor 2 scores of file-only reviews to be two points lower than standard assessments. One study indicated that doing the full procedure versus doing the file-only review produced less than desirable correspondence between the two methods, but there was no clear evidence of underestimation in the file-only condition (Serin, 1993). The predictive accuracy of the PCL: SV file review seems to differ only according to the type of records being used. Studies have found that there was no correlation between the PCL: SV and the outcome of violence when psychiatric records were used, but found a strong correlation when relying solely on criminal records (Douglas & Ogloff , 2003).

In conclusion, the advantage of doing a file-only review offers a quick means for gathering information, but the disadvantage is that files may not have sufficient information regarding personality traits (e.g., glibness and grandiosity, etc.); in addition, the scores may be lower than they would be on standard assessments.

PCL-R Item Content

Utilizing the two-factor model of psychopathy, Factor 1 of the PCL-R assesses personality characteristics (interpersonal and affective traits) of the individual and encompasses Items 1, 2, 4, 5, 6, 7, 8, and 16 on the rating scale. This constellation of traits describes the interpersonal and affective traits fundamental to the construct of psychopathy. These items require clinical inferences about individuals' affective processes and interpersonal styles (Hare, 2003). Factor 2 of the PCL-R assesses behavior patterns and is assessed by Items 3, 9, 10, 12, 13, 14, 15, 18, and19 on the rating scale. These nine items reflect a chronically unstable, antisocial, and socially deviant lifestyle. Two of these items (Items 18 and 19) reflect criminal behavior and the other seven describe the aimless, impulsive, irresponsible, and parasitic behaviors common to psychopaths. All items on the PCL-R are further elucidated in Table 1.

PCL:SV.

Although the PCL-R is considered the "gold standard" (Edens, Skeem, Cruise, & Cauffman, 2001) in forensic literature and practice, one of its primary drawbacks is the time required to complete the interview and file review. Each interview takes approximately 1.5 to 2 hours to complete, but the file review takes about 20 minutes for experienced users (Hare, 1990). To address this resource-intensive issue, Hart, et al., (1995) developed a derivative of the PCL-R, called the PCL: SV.

The PCL: SV is 40%-50% shorter than the PCL-R (Hart, Hare, & Forth, 1994;

as pathological lying versus manipulation, shallow affect versus lacks empathy and other items that require great detail for scoring and involve difficulty in judging (e.g., promiscuous sexual behavior and parasitic lifestyle). The two factors of the PCL: SV are labeled Part I and Part II and are analogous to Factor 1 and Factor 2 respectively on the PCL-R (Hart et al., 1995). Both the PCL-R and the PCL: SV have shown good psychometric properties and predictive validity for institutional violence (Cooke, 1998; Hill, et al, 1996).

PCL:SV Item Content

The 12 items of the PCL: SV for rating traits and behaviors of psychopathy include similar items to the PCL-R. The PCL: SV differs from the PCL-R in that there are fewer items because highly specific items or difficult to confirm items (e.g., sexual history) were removed (Hart, et al., 1995).

The PCL: SV includes the following items: Superficial, Grandiose, Deceitful, Lacks Remorse, Lacks Empathy, Does Not Accept Responsibility, Impulsive, Poor Behavioral Control, Lacks Goals, Irresponsibility, Adolescent Antisocial Behavior, and Adult Antisocial Behavior. The PCL: SV is a guided or structured clinical assessment, blending actuarial and clinical means for data acquisition and assessment. The manual requests that the evaluator use these traits not as a list of symptoms but rather as a means to build a prototype or ideal image of the item and then rate the individual according to how closely he or she matches this prototype.

Table 1

PCL-R Items for Diagnosing Psychopathy

Item Number and Title	Description
1. Glibness/Superficial Charm.	The individual tries to make a favorable impression, may appear smooth and smart, or may impress by the appearance of being sullen, hostile or "macho." The person may tell unlikely but convincing stories and use technical words confidently. The individual may be engaging and likeable, but too slick and smooth to be believable.
2. Grandiose sense of worth	This trait is evidenced by inflated self-worth and an attitude of superiority. Typically, persons who are grandiose do not feel embarrassed about their legal situations and believe they are due to something outside of their control (e.g. bad luck; incompetent police).
3. Need for Stimulation	This is seen as a chronic need for novel and exciting stimulation. The person is said to live in the fast lane or to be living on the edge.

Table 1 (Continued)

PCL-R Items for Diagnosing Psychopathy

Item Number and Title	Description
4. Pathological lying	This individual confidently and unabashedly lies and if caught will attempt to rework the facts to be more consistent.
5. Conning/Manipulative	The individual lies, cheats, defrauds or manipulates others for personal gain.
6. Lack of remorse or guilt	Individuals have no concern for or insight into the negative impact their actions have on others. In fact, the perpetrators with no remorse may blame the victim for what has occurred.
7. Shallow affect	The individual with shallow affect lacks the normal breadth or depth of emotions. There might be a display of emotion which may be dramatic in appearance but is basically shallow and short-lived.
8. Callousness/Lack of empathy	The individual is cynical and selfish, and has no regard for the welfare of others.

Table 1 (Continued)

PCL-R Items for Diagnosing Psychopathy

Item Number and Title	Description
9. Parasitic lifestyle	The individual depends financially on friends and family. The individual may present as helpless or deserving of sympathy or support, but never holds gainful employment.
10. Poor behavioral control	The person with poor behavioral control is short-tempered and will inappropriately respond to frustration or criticism with threatening or violent behavior.
11. Promiscuous sexual behavior	Sexual relations are impersonal and indiscriminant. The individual may coerce others into sexual activity.
12. Early behavioral problems	There is a history of serious behavioral problems before age 12. Examples of serious behavioral problems include theft, fire-setting, truancy, substance abuse, school disruption, and running away.

Table 1 (Continued)

PCL-R Items for Diagnosing Psychopathy

Item Number and Title	Description
13. Lack of realistic long-term goals	An individual may have an inability to form goals and carry them out. Alternatively, the individual may have goals but they may be unrealistic. Often individuals will have get-rich-quick schemes.
14. Impulsivity	Actions performed on the "spur of the moment" and without concern for consequences are indications of impulsivity.
15. Irresponsibility	Irresponsibility is demonstrated by the lack of duty or of loyalty to others. If commitments are made, typically there is no follow through. Irresponsibility may show up in financial dealings, in work behaviors, in relationships, and in putting others at risk (e.g., driving drunk or recurrent speeding with others in the car).
16. Failure to accept responsibility for one's own actions	This trait is indicated by use of excuses: the individual may rationalize, blame, and deny. If the person accepts responsibility, it is in a superficial manner.

Table 1 (Continued)

PCL-R Items for Diagnosing Psychopathy

Item Number and Title	Description
17. Many short-term relationships.	For this item to apply, a person's history must be marked by many marriages or live-in relationships.
18. Juvenile delinquency	A history of serious antisocial behavior before age 17 must be evident.
19. Revocation of conditional	After the age of 18 there is a pattern of violation of conditional release or of escapes from institutions
20. Criminal versatility	Criminal versatility is indicated by criminal records that show a *variety* of offenses. Regardless of the number of times an individual is arrested, if the arrests are for the same one or two types of offense repeatedly, versatility is not indicated.

Criticism and Appeal of the PCL-R

Even though there is wide acclaim for the PCL-R, it is not without its shortcomings. It has been claimed that the PCL-R is an atheoretical measure of psychopathy not only because it has deviated from Cleckley's conceptualization of psychopathy, but also because the characteristics were based only on literature reviews and practical experience (Salekin, et al., 1996). Another criticism is that the inclusion of

affective and interpersonal features is that which distinguished the criteria of the PCL-R from that of the *DSM*; it is given no special significance or weight on the instrument (Kosson, Steuerwald, Forth, & Kirkhart, 1997).

The appeal of the PCL-R is that it has shown a stable factor structure, good interrater reliability and test-retest reliability; predictions of violence using the PCL-R appear to be as good and in some cases better than existing measures (Hare et al., 1990; Harris, Rice, & Cormier, 1991; Hart, et al., 1995; Webster, Harris, Rice, Cormier, & Quinsey, 1994). It has been considered the best developed instrument for the assessment of psychopathy among correctional populations (Hare, 1980; 1985).

Psychological Inventory of Criminal Thinking Styles

Theoretical Foundation

The PICTS is an assessment with theoretical roots in social learning theory and the criminal lifestyle model. It was devised to measure thinking styles supportive of a criminal lifestyle (Walters, 1990). In this criminal lifestyle model, instead of personality defining the lifestyle, behavioral patterns are the key elements (Walters & Di Fazio, 2000). Antisocial behavior in this model is measured by the level of involvement in, commitment to, and identification with a prototypic criminal lifestyle. In contrast to focusing on personality disturbance, the criminal lifestyle theory maintains the following: (a) that patterns of behavior and not the person are labeled (to avoid the self-fulfilling prophecy that the labeling process promotes) (Walters & De Fazio, 2000); (b) the focus is on bi-directional and reciprocal relationships avoiding biological determinism; (c) criminality is a dimensional construct not a dichotomy—the behavioral styles are postulated to fall along a continuum, whereby the extent to which they become habitual marks the severity of the criminal lifestyle (Walters & Di Fazio, 2000); and (d) that change is possible (Walters, 2004).

Thus, chronic criminal behavior is not viewed as a personality disturbance but as an investment in and commitment to the identity of a criminal lifestyle. Investment and commitment to this identity then become the template for future decisions and actions. If nothing changes, criminal behavior becomes a way of life. The PICTS is an instrument that measures ideation related to a criminal lifestyle, but it is also an instrument that is sensitive to change. Because of this specific attribute, the PICTS has been researched for the Prison Service of England and Wales and is recommended for measuring changed attitudes during imprisonment (Palmer & Hollin, 2003).

Development of a criminal lifestyle is influenced by the “three C’s”: conditions, choices, and cognitions (Walters, 1990). It is important to note the three C’s are not determinants of behavior but that they establish vulnerability for the criminal lifestyle

(Walters, 1990). 'Conditions' include internal (e.g., heredity, intelligence), external (e.g., family, peers), and interactive (person by situation) elements. 'Choice' derives from the available options present, and 'cognitions' involves the thinking style that rationalizes and justifies criminal behavior (Walters, 1990).

Cognitions are the focus of the PICTS. Cognitions are associated with criminal behavior and arise from belief systems which underlie the way criminals view themselves, the world, and the interaction between themselves and the world (Walters, 1998). To understand what maintains criminal behavior, it is critical to look at the beliefs underlying criminals' thoughts. The PICTS is an instrument that was designed to assess the dysfunctional beliefs, or errors of thinking, in individuals pursuing a criminal lifestyle (Walters, 1990).

Basis of Thinking Styles

Chronic criminality can be postulated as a lifestyle characterized by four primary behavioral markers: a global sense of irresponsibility, self-indulgent interests, an intrusive approach to interpersonal relationships, and chronic violation of social rules, laws, and mores (Walters, 1990). Because thinking styles are fundamental to cognitive theory, Walters suggests that they are related to criminal lifestyle behavior. These thinking styles, which are faulty and irrational, have the effect of buttressing the individual's criminal decisions (Walters, 1990; Walters & White, 1989). Eight patterns of thinking are linked with the four behavioral markers of lifestyle criminality.

Irresponsibility. The first behavioral marker is irresponsibility, which refers to the disinclination of the individual to account for his or her conduct and obligations. For example, irresponsibility is indicated by non-support of a child. Behaviors indicating irresponsibility are associated with two cognitive errors, Cognitive Indolence (Ci) and Discontinuity (Ds). Cognitive indolence involves using short cuts uncritically, in lieu of problem solving. Individuals who score high on Ci are often characterized as lazy and unmotivated. An example of an item on the PICTS assessing Ci is, "I tend to act impulsively under stress." The second cognitive error related to irresponsibility is Discontinuity (Ds). Discontinuity presumes less premeditation than Ci; the result is an individual who has difficulty following through on good intentions. Individuals scoring high on the Ds scale are viewed as fragmented, flighty, and unpredictable. An example of an item on the PICTS that assesses Ds is: "Even though I may start out with the best of intentions I have trouble remaining focused and staying 'on track,'" (Walters, 1990).

Self-Indulgence. The second behavioral marker of criminality is self-indulgent interests, which results in a pursuit of personal pleasure with the lack of concern for the negative long-term consequence. For example, self-indulgence is indicated by a history of drug and alcohol abuse. The cognitive errors associated self-indulgence are Sentimentality (Sn) and Superoptimism (So). Sentimentality entails performing good deeds in order to feel like a "good guy." Those scoring high on Sn often do not see the harm they have inflicted on themselves and others because sentimentality blocks insight. In order to assess Sn, the PICTS includes items such as "I have helped out friends and family with money acquired illegally." Superoptimism is an unrealistic underestimation of "getting caught," so that when friends are being arrested and imprisoned there is little impact because the individual believes he or she will avoid such a fate. The PICTS assesses So with items such as "The more I got away with crime the more I thought there was no way the police or authorities would ever catch up with me" (Walters, 1990).

Interpersonal intrusiveness. The third behavioral marker of a criminal lifestyle is interpersonal intrusiveness, or infringing on the rights of others. For example, use of a weapon during the confining offense is interpersonal intrusiveness. Entitlement (En) and Power Orientation (Po) are the cognitive styles associated with interpersonal intrusiveness. Entitlement presumes a sense of privileged status and the special right to satisfy one's own desires at the expense of others. A sample item on the PICTS assessing En is, "When it's all said and done, society owes me." Power Orientation (Po) involves putting others down as a means of feeling good about oneself and in violating their spaces to feel in control. These individuals are referred to as "control freak"; when not in control they feel weak and powerless. PICTS assesses Po using items such as, "When not in control of a situation I feel weak and helpless and experience a desire to exert power over others" (Walters, 1990).

Social rule breaking. The fourth behavioral marker of lifestyle criminals is social rule breaking. This is a general disregard for societal norms, values, and mores and is indicated by a history of prior arrests. The cognitive styles that are associated with social rule breaking are Mollification (Mo) and Cutoff (Co). Mollification is justifying and rationalizing rule-breaking behavior by placing blame on others or on the situation.

An item from the PICTS that assesses Mo is “I have found myself blaming the victims of some of my crimes by saying things such as ‘they deserved what they got’ or ‘they should have known better.’ Cutoff means eliminating deterrents that block the commission of a crime, typically with a short saying like “screw it” when frustrated. Drugs and alcohol are another popular form of cutoff (Walters, 1995). A sample item assessing Co on the PICTS is “When pressured by life’s problems I have said, ‘the hell with it’ and followed this up by using drugs or engaging in crime” (Walters, 1990).

Other PICTS Scales

The PICTS assesses the eight thinking styles associated with the four behavioral markers. In addition to assessing these thinking styles, there are a number of other scales assessed in the PICTS: four primary factor scales, two content scales, three validity scales, and two composite scales (P and R).

Four primary scales. An exploratory factor analysis has reassembled the eight thinking styles into four primary factors. These four primary factors are: Problem Avoidance (PRB; running from problems), Interpersonal Hostility (HOS; extreme hostility leading to confusion), Self-Assertion/Deception (AST; asserting one’s will over others without regard for others), and Denial of Harm (DNH; rationalizing and minimizing harm) (Walters, 1995).

Two content scales. Two content scales, Current (CUR) and Historical (HIS) scales were created to reflect stability and change of thoughts and actions. Items in the past tense section were considered stable and those written in present tense were designed to make the inventory sensitive to change. An example from the CUR Scale is, “I find myself taking shortcuts, even if I know these shortcuts will interfere with my ability to achieve certain long-term goals;” and an example from the HIS scale is “When questioned about my motives for engaging in crime, I have justified my behavior by pointing out how hard my life has been” (Walters, 2001a; 2002).

Three validity scales. Three validity scales are incorporated into the PICTS. They are the revised Confusion scale (Cf-r-t), the revised Defensiveness scale (Df-r) and the “?” scale. The Cf-r-t scale is designed to identify a “fake bad,” malingering, or “yea-saying.” An example of an item from the Cf-r-t, includes: “Strange odors, for which there is no explanation, come to me for no apparent reason.” The Df-r scale is sensitive to “fake good” response sets, and includes items such as “I have made mistakes in life.” The last validity scale, “?”, refers to the number of omitted items. More than five omitted items signifies an invalid profile (Walters, 2001a).

P and R scales. The PICTS P and R scales are newly researched categories of general ideation. The PICTS Proactive (P) scale appraises general criminal thinking of a planned nature. Here, thinking is directed toward an end goal (is instrumental) and there is anticipation of the future benefits of the behavior (or crime). The Reactive (R) scale evaluates general criminal thinking that is impulse driven, emotional, and often in response to another person’s actions or situational factors (Walters, 2005a).

The P and R scales are regarded as composite scores because they are composed of other PICTS scales. The P and R scales include two Primary scale scores (the AST and PRB, respectively), two thinking styles (the En and Co, respectively), and two

Content Scales (the HIS and CUR, respectively) (Walters, 2005b). AST and PRB scale scores are each composed of several thinking styles. PRB consists of the thinking styles Co, Ci, and Ds to reflect impulsive, irresponsible and anemic life direction, which is characterized by reactive aggression. AST is composed of Mo, En, and So thinking styles, which indicate a desire to exert one's will over the environment, to justify one's actions with excuses and rationalizations, and a sense of having an invulnerability to being found out. These denote a presence of instrumental or proactive motives (Walters, in press c).

Formulas with weighted scores provide the means for arriving at the P and R general ideation scores. The following are the formulas from which the P and R scales are derived (Walters & Geyer, 2005):

P = (En x 2) + (AST x 1.5) + HIS

R = (Co x 2) + (PRB x 1.5) + CUR

Criticism and Appeal of the PICTS

The use of P and R scales for predicting inmate adjustment is still developing and consequently has not been widely used to date. The fact that the PICTS is a self report measure used in offender population and relies on honesty, motivation, and reading ability has drawn concern (Edens, et al., 2000). The appeal of the PICTS is that it is a self-report instrument allowing for less intensive demand on time, staff, and financial resources.

Prediction Studies using the PICTS and PCL

Prediction Studies and the PCL

An overview and analysis of eighteen studies, published between 1974 and 1995, that have used PCL-related instruments for predicting violent behavior yielded 29 effect sizes, indicating that the PCL-R as a predictor of violence had moderate to strong effect sizes (Salekin, et al., 1996). This analysis also revealed the PCL: SV produced the largest effect sizes when compared with the other PCL progeny. In another study, Monahan et al. (2001) examined the predictive validity of the PCL: SV in a population of 871 civil psychiatric patients and found a 73% chance that a patient who becomes violent will obtain a higher score on the PCL:SV. The correlations in several studies varied: one study found r values less than .20 between psychopathy and aggression (Edens, et al., 1999; Heilbrun, et al., 1998; Edens, Petrilla, & Buffington-Vullum, 2001). Hildebrand et al. (2004) found the PCL-R was more strongly related to total aggression (verbal and physical) than for physical aggression alone. Here, $r = .44$ for total aggression and $r =.03$ for physical aggression were found. Another study demonstrated the following significant correlations between the PCL-R and aggression: total aggression ($r = .31$), assaults on staff ($r =.24$), assaults on inmates ($r = .15$), and for property damage ($r = .18$) (Hare, et al., 2000).

Prediction Studies and the PICTS

The PICTS has shown success in predicting behavior. Studies on female and male inmate populations indicated that the PICTS scales were correlated with both recidivism and future disciplinary infractions (Walters, 2002; Walters & Elliott, 1999). The thinking styles correlated more with Factor 2 than Factor 1 of the PCL-R (Walters, in press d) suggesting the thinking styles are more closely associated with an antisocial lifestyle than with interpersonal and affective characteristics of psychopathy.

The particular scales within the PICTS considered most effective in forecasting adjustments are the P and R criminal thinking composite scales. The proactive-reactive model of aggression was proposed by Dodge and Coie (1987) and subsequently applied to criminal thinking styles by Walters (in press c). Proactive aggression is regarded as cold blooded, offensive, and goal directed; reactive aggression is hot blooded, defensive, and impulsive (Walters, in press c). A high correlation exists between these two types of aggression (Dodge & Coie, 1987) but they have shown association with unique criminal variables (Walters, Frederick, & Schlauch, 2005). Scores on the PICTS P scale correlated with prior arrests for instrumental aggression, such as robbery and burglary; however, scores on the PICTS R scale correlated with prior arrests for reactive aggression (assault, domestic violence) (Walters, et al., 2005).

In a number of studies the P and R scales have produced stronger correlations than the individual thinking style scales in predicting institutional adjustment and recidivism (Walters, 2005b; Walters, in press a; in press c). Walters and Geyer (2005) have shown that the PICTS R scale which measures thinking that is reactive and poorly planned correlates with institutional misconduct. Significant correlations between the PICTS R and adjustment suggest *r* values that range from .21 to .31 for total incident reports; *r* values that range from .14 to .26 for aggressive incident reports; and *r* values that range from .20 to .29 for non-aggressive incident reports (Walters, 2005a, 2005b, in press d; Walters & Geyer, 2005). Significant correlations between the PICTS P and incident reports showed a range of *r* values from .14 to .16 for total incident reports, and an *r* =.14 for non-aggressive incident reports (Walters, 2005a, 2005b, in press d; Walters &Geyer, 2005). It has been suggested that prison misconduct is situational and reactive (Toch & Adams, 2002). This is corroborated by the findings that the PICTS R scale has consistently shown correlation with incident reports (total, aggressive, and non-aggressive) (Walters, 2005b; Walters, in press d; Walters & Geyer, 2005). The PICTS P scale has shown less consistency but nonetheless has been correlated with total and non-aggressive incident reports (Walters, in press d; Walters & Elliott, 1999).

Conclusion

There are a number of tools available for assessing risk. Two which are the focus of this study are the PCL:SV and the PICTS. The PCL:SV is risk assessment instrument measuring psychopathy and the PICTS is a self-report instrument measuring thinking styles. Self-report instruments, such as the PICTS, assess test-taker’s conscious understanding of themselves; although they are resource friendly they are limited by individuals’ motivation to communicate honestly and their ability to make accurate judgments. Clinician rated instruments, such as the PCL:SV, elicit the raters' perceptions of the individuals, but the raters are constrained by the parameters of the information provided in the file. It has been suggested that the optimal methodology to clinical assessment consists of combining data from various methods and multiple operational definitions (Meyer, et al., 2001) because a single method regularly results in faulty conclusions (Fennig, Craig, Tanenberg-Karant, & Bromet, 1994). Thus, the combination of measures such as the PICTS and PCL:SV may enhance and improve assessment and prediction of prison adjustment.

Developing the Research Hypotheses

The focus of this study was to investigate the incremental validity for predicting prison adjustment over a 12 month period. Both the PICTS, a self-report instrument, and the PCL:SV, a clinician rated instrument, have shown effectiveness at predicting prison adjustment. Although particular elements of each (i.e., the PICTS R composite scale and PCL:SV Total scale) demonstrated stronger ability for predicting disciplinary infractions than others, these particular elements have not yet been explored further for possible incremental validity.

Studies of incremental validity investigate whether or not the addition of one set of information to another set of information leads to an increase in validity. For example, a test score that is statistically significant or even one that is not statistically significant alone, when added to other assessment information, may produce a significant increase in validity (Meehl, 1959; Sechrest, 1963). It has been suggested that the combined use of measures might in fact prove more useful for classifying purposes than one instrument alone (Buffington-Vollum, Edens, Johnson, & Johnson, 2002). Sechrest (1963), who introduced the concept of incremental validity, noted that an added measure should contribute to the predicted outcome beyond the information that the ordinarily used predictors contribute, in addition to the researcher keeping in mind the ease and cost of the added measure. The use of incremental validity has been more prevalent in academic performance (e.g., prediction of grades in college) than in research (Sechrest, 1963). As a result little research has been conducted measuring incremental validity, but there is a growing interest (Garb, 2003). The benefits of investigating incremental validity could improve both practice and predictions.

This study is an exploration of incremental validity between the PCL:SV Total score, a risk-appraisal measure and the PICTS R scale score, a self-report measure in predicting disciplinary adjustment among male inmates over the first 12 months at the study site. Adjustment is defined by frequency of incident reports which were disaggregated into aggressive and non-aggressive categories. The PICTS R scale reflects cognitive activity occurring in response to environmental stress and is correlated with hostile attributional biases (Walters, et al., 2005). Because the PICTS R scale is reactive and poorly planned it should correlate better with institutional misconduct which is situationally specific and impulsive than it would for misconduct that is goal directed, as assessed by the P scale. The PICTS P scale is associated with entitlement thinking style and is correlated with positive outcome expectancies for crime. It is included in this study for exploratory purposes because it has also shown a relationship, albeit less consistent than the R scale, with inmate adjustment (Walters, 2004, 2005a).

Research Hypotheses

The following are the hypotheses for this study:

1. Age will be inversely related to number of infractions.
2. Years of education will be negatively correlated with number of prison infractions.
3. Ethnic status will be correlated with number of infractions. More specifically, nonwhite inmates will be correlated with a higher number of infractions.
4. Single marital status will be correlated with a higher number of infractions than non-single marital status.
5. Inmates with violent confining offenses are expected to have more incident reports than inmates with non-violent confining offenses.
6. The PCL:SV (Total, Part I, and Part II) will have a positive correlation with incident reports.
7. The PICTS (P and R scales) will have a positive correlation with incident reports.
8. The PICTS R Scale will produce incremental validity relative to the PCL:SV in predicting incident reports.

CHAPTER 3

METHODOLOGY

Participants

Participants for this study were 146 male inmates who had arrived between August, 2003 and March, 2004 at a medium security, federal correctional institution located in Pennsylvania. Currently there are approximately 1,277 male inmates housed at this facility (Federal Bureau of Prisons, 2005). Data for this study were collected from electronic and paper files; there was no direct contact with inmates.

New admissions to the institution routinely take the PICTS as part of the entrance procedures. The scores for the PICTS and the disciplinary report data were retrieved from federal electronic files, and the data for the PCL:SV rating scale was derived from paper files which were housed in the records department on the facility grounds. A staff correctional psychologist assigned numbers chronologically to participants' data files (i.e., demographics and PCL:SV data) when transferring them to computer files in preparation for statistical analyses. Any data identifying an inmate's family name, social security number, inmate number, or other uniquely identifying information were retained at the facility. Data leaving the institution had all identifying information removed.

Inclusion/Exclusion Criteria

Participants included in the study had valid scores on the PICTS and sufficient chart data to score the PCL:SV. A valid profile was defined as a PICTS record that had no more than 10 omitted items and a *T*-score on the Cf-r-t validity scale ≤ 100 (liberal criteria to maximize the number of study participants).

Seven inmates were excluded because five inmates had invalid PICTS scores and two inmates had insufficient chart data to score the PCL:SV, leaving a sample of 146 participants.

Measures

The Psychopathy Checklist: Screening Version

The PCL:SV is a 12-item symptom rating scale that is 40% shorter than the PCL-R from which it was derived. The PCL:SV was designed as a screening method for psychopathy; if an individual scores high enough on this instrument, it is suggested that the full PCL-R assessment be administered (Hart, et al., 1995). The PCL:SV and the PCL-R are conceptually and empirically related; they have demonstrated similar psychometric properties, producing a weighted mean correlation of .80 across samples (Cooke, Michie, Hart, & Hare, 1999; Hart et al., 1995).

There are two parts to the PCL:SV. Part I is analogous to the PCL-R Factor 1 and assesses psychopathic affective and interpersonal behavior. The six items in Part I are titled Superficial, Grandiose, Deceitful, Lacks Remorse, Lacks Empathy, and Doesn't Accept Responsibility. Part II, which is analogous to the PCL-R Factor 2, assesses psychopathic behavior and includes six items: Impulsive, Poor Behavioral Controls, Lacks Goals, Irresponsible, Adolescent Antisocial Behavior, and Adult Antisocial Behavior.

The 12 items on the PCL:SV are scored on a 3-point rating scale: 0 = No (the item does not apply to the individual); 1 = Maybe (the item applies to a certain extent) and; 2 = Yes (the item applies to the individual). If records provide insufficient information, up to two items on the checklist may be omitted and the score prorated. The PCL:SV technical manual (Hart et al., 1995) notes that the PCL:SV can be scored by a trained professional in 20-30 minutes.

Three scores are produced on the PCL:SV: total, Part I, and Part II scores. The total score reflects the overall symptomatology, and range from 0-24. Part I scores indicate the severity of interpersonal and affective symptoms, and range from 0-12. Part II scores reflect the severity of social deviance, and range from 0-12. The PCL:SV technical manual (Hart et al., 1995) describes the total score as a measure of the person's likeness to the prototypical profile of a psychopath. A "best" cutoff score is not offered; however, a recommended score of ≥ 18 is provided.

The PCL:SVmanual (Hart et al., 1995) notes that a cutoff score ≤ 12 yields nearly 100% specificity that psychopathy is not present. A score ≥ 18 has a sensitivity rating of 100% with a specificity of 82%. A ROC curve analysis in one study indicated that with a cutoff of 18 the true positive rate is 81% and the false positive rate is 15% (Cooke, et al., 1999).

Psychometric Characteristics

Psychometric characteristics refer to the evidence demonstrating the reliability and validity of a measure. Reliability refers to the consistency of the measure within itself (internal consistency), across raters (interrater reliability), and over time (test-retest reliability). Validity refers to the content and determines whether or not the measure assesses the domain of interest. This encompasses the extent to which a measure correlates with other instruments that assess the same construct (convergent validity) and fails to correlate with instruments that assess different constructs (divergent validity). Validity also encompasses the extent to which the performance of one measure compares to the performance of other related measures at the same time (concurrent validity).

Internal consistency. The overall internal consistency of the PCL:SV total scores averaged .84. Cronbach's alphas for Part I and Part II were .81 and .75 respectively. These lower alphas are expected because alpha is related to scale length.

Interrater reliability. Although the PCL:SV is called a checklist, the items should not be used as a simple checklist (Hart et al., 1995). It is suggested that raters score the items according to the manner in which the individual has functioned *on average* throughout his or her lifespan in comparison with a prototypical psychopath (Hart et al., 1995). Because human judgments have measurement error that can seriously affect data analysis and interpretation, it is important to obtain an index of reliability. Inter-rater reliability is a measure of the extent of consensus between test scorers. For this study, a staff psychologist from the federal correctional institution certified in the administration and scoring of the PCL:SV scored 25 files that had already been scored. Intraclass correlation (ICC) was used to measure inter-rater reliability. The one-way random effect model and the single measure of reliability were used because: (a) the design was a one way ANOVA, (b) raters were considered random, and (c) the unit of analysis was a single rater (Shrout & Fleiss, 1979). Two coefficients were supplied: the single measure ICC, which is the index of the reliability of the ratings for one judge, and the average measure ICC, which is the reliability of both judges averaged together.

For the PCL:SV total, the single ICC was .76 and the average was .86 at the 95% confidence interval. For the PCL:SV Part I, the single measure ICC was .63 and the average measure ICC was .77 at the 95% confidence interval. For the PCL:SV Part II, the single measure ICC was .62 and the average measure ICC was .77 at the 95% confidence interval. These results suggest moderate inter-rater reliability. The PCL:SV total inter-rater correlations were a little lower than were those found in the PCL:SV technical manual (Hart et al., 1995); however, they were still comparable.

The PCL:SV manual (Hart et al., 1995) indicates that in the case of 586 subjects from 11 different samples, the interrater reliability measured by ICC for one rater was .84, .77. and .82 for total, Part 1, and Part II, respectively, and for two raters the ICC was .92, .88, and .91 for total, Part I, and Part II, respectively.

Test-retest reliability. No test-retest studies have been completed using the PCL:SV. Hart et al. (1995) used the Spearman-Brown formula and the test-retest reliability of the PCL-R to estimate the reliability of the PCL:SV. The formula resulted in r =.90 as an estimate of the 1-month test-retest reliability of the PCL:SV.

Convergent and discriminant validity. Validation of the PCL:SV was derived from a sample of 586 subjects across eleven samples and four settings (correctional offenders, forensic psychiatric patients, civil psychiatric patients, and university students) as part of the MacArthur Risk Study (Steadman, et al., 1994). Convergent and discriminant tests of validity were established to assesses the relationship of the items on the PCL:SV to the concept of psychopathy. Convergent validity of the PCL:SV was established by testing the PCL:SV against the Personality Disorder Examination (Loranger, 1988), a clinical-behavioral measures of the *DSM-III-R* personality disorders, and the MCMI-II (1987), a self-report measure of psychopathology. Total scores were positively correlated with the Cluster B (dramatic-erratic-emotional) antisocial (r =.74), narcissistic (r =.58), histrionic (r =.45), and borderline personality disorders (r =.48), and also positively correlated with passive-aggressive (r =.54) and sadistic personality disorder (r =.47) (Hart et al., 1995). To establish further convergent validity, the PCL:SV was compared with the Interpersonal Adjective Scales (Wiggins, Trapnell, & Phillips, 1988) to distinguish the difference between psychopathy and normal personality. The PCL:SV total score was negatively correlated with Conscientiousness (r = -.74) and Openness (r = -.48), and correlated positively with Dominance (Hart et al., 1995). For discriminant validity, the PCL:SV total score did not correlate significantly with the BDI, STAI-State, or STAI-Trait (*r* =.05, .06, and .06 respectively). Thus, the ratings do not appear to be influenced by mood states.

Concurrent validity. Regarding concurrent validity, a type of criterion related validity, the PCL:SV was compared with self-report measures of psychopathy/antisocial personality disorder. The PCL:SV was correlated with independent antisocial personality disorder ratings in six samples; one of the correlations included federal inmates, *r* =.62. Overall, the correlations between the PCL:SV and three self-reports were moderate to large in magnitude (Hart et al., 1995).

Psychological Inventory of Criminal Thinking Styles

The PICTS consists of the following scales: (a) two validity scales called Confusion-revised (Cf-r-t) and Defensiveness-revised (Df-r); (b) eight thinking styles scales which include: Mollification (Mo), Cutoff (Co), Entitlement (En), Power Orientation (Po), Sentimentality (Sn), Superoptimism (So), Cognitive Indolence (Ci), and Discontinuity (Ds); (c) two content scales titled Current Criminal Thinking (CUR) and Historical Criminal Thinking (HIS); (d) four factor scales which include: Problem Avoidance (PRB), Interpersonal Hostility (HOS), Self-Assertion/Deception (AST), and Denial of Harm (DNH); and recently added (e) two composite scales, the Proactive Criminal Thinking (P) scale and the Reactive Criminal Thinking (R) scale (Walters, in press c).

The PICTS consists of 80 items written at a sixth grade reading level, requiring about 20-30 minutes for completion. The items on the instrument are rated on a four-point scale: 1 = disagree, 2 = uncertain, 3 = agree, and 4 = strongly agree.

Psychometric Characteristics

Internal consistency. The internal consistency and stability of the PICTS validity scales, thinking style scales, factor scales, content scales and special scales indicated Cronbach's alphas in the .55-.88 range for males. Cronbach's alpha $\geq$ .75 was found for Co, Ci, and Ds thinking styles and Cronbach's alpha ranges from .55 to .65 for the remaining thinking styles. Mean inter-item correlations were between .13 and .39 (Walters, 2001a).

Test-retest reliability. The test-retest stability coefficients for all the scales at two weeks exceeded .70. After 12 weeks it was above .50 with only two correlations below .50. These findings indicated that the PICTS possesses moderately high test-retest stability after two weeks and moderate test-retest stability after twelve weeks (Walters, 1995).

Concurrent validity. Comparing the PICTS to prior criminality and other measures of criminal/antisocial status assessed concurrent criterion-related validity. The PICTS scales correlate from modestly to moderately with past criminality; the Historical content scale providing the strongest overall association with prior criminality (ranging across factors r = .20 to -.32). The PICTS was moderately correlated with the Lifestyle Criminality Screening Form (Walters, 1998; Walters, 2001a) and the PCL-R.

PICTS validity scales have been correlated with the PAI validity scales (Walters & Geyer, 2005). Cf-r-t scale correlated positively with the PAI Negative Impression scale, r = .45 and negatively with the PAI Positive Impression scale r = -.50. The Df-r scale correlated positively with the PAI Positive Impression scale, r = .43 and negatively with the PAI Negative Impression scale, r = -.23 (Walters & Geyer, 2005).

Adjustment Measure

There are several hundred rule violations that serve as the foundation for the disciplinary reports outcome. The Federal Bureau of Prison has kept an active computerized file since the early 1990's, cataloguing all disciplinary reports received by inmates. Inmates received disciplinary reports after being found guilty by the Disciplinary Hearing Officer (who serves as a kind of judge). This officer determines whether or not the disciplinary report has validity and subsequently finds the inmate either guilty or innocent of the charges. Disciplinary reports were divided into aggressive and nonaggressive categories, in lieu of using a single index for incident reports in the present study. Aggressive disciplinary reports were reports received for fighting, assault, and threatening. All other disciplinary reports were considered non-aggressive incident reports.

Procedures

Data Collection

All information was gathered either from the inmates' prison files or from archival sources. Because this was a purely archival study using preexisting information, informed consent procedures were not necessary. Permission was granted by the correctional facility to use inmate records for research purposes.

PICTS

PICTS data were collected from the computer database for inmates arriving between August 2003 and March 2004. Inmates routinely take the PICTS as part of the psychology services intake process at this federal correctional institution. The PICTS was electronically scored and raw scores were converted into a standard *T* score for norming.

PCL:SV

The PCL:SV scores were derived exclusively from inmates' charts called presentencing investigation files. The PCL:SV QuikScore form was used as a score sheet for the ratings. Scoring from file data, exclusively, is acceptable when the standard procedure of conducting interviews cannot be completed (Hart et al., 1995). One advantage in using only record data is the ability to gather data quickly.

Two raters received extensive training in the use of the PCL-R by completing PCL-R ratings, using 10 case-study videos and the accompanying file summaries made available by Dr. Robert Hare. After this training, using only the presentencing file information, one rater completed PCL:SV ratings on 146 cases, and the other rater independently rated 25 cases.

Disciplinary Reports

Disciplinary reports data were retrieved from the Federal computer files. Disciplinary reports included counts of aggressive or threatening verbalization, violent behavior, and treatment compliance for each inmate. Disciplinary adjustment data were collected for 12 months following administration of the PICTS.

Data Analysis Plan

The present study investigated the incremental validity of the PICTS R scale relative to the PCL:SV total scale since both the PCL:SV total scale and the PICTS R scale have each shown moderately good ability for forecasting inmate adjustment (Monahan, 2001; Walters & Geyer, 2005). It was predicted that by combining these psychometric measures they would produce an increased ability in predicting adjustment.

The variables in this investigation included participant demographics, psychometric variables, and criterion variables. The relationships between the control and predictor variables with the criterion variable were analyzed thorough the use of a series of correlational analyses. The level of data represented by these variables was reviewed prior to analysis. The psychometric scores from the PCL:SV and the PICTS were regarded as continuous ordinal data. The demographic variables were represented either as continuous ratio data (for age and years of education) or as dichotomized nominal data (white versus nonwhite for ethnic status; single versus not single for marital status; and aggressive versus non-aggressive for confining offense). The criterion variable, the number of disciplinary reports, was represented both as dichotomized nominal data (e.g., received infractions versus did not receive infraction) and as discrete ratio count data (number of incident reports received).

In the preliminary investigation, five demographic variables were assessed to determine their relationship with the criterion variable; these included age, education level, ethnic status, marital status, and type of confining offense. Those demographic variables that correlated with the criterion variable were used in the subsequent regression analyses as control variables.

Following the preliminary investigation, regression analysis was used to assess the relationships between the predictor variables and criterion variable. Five predictor (independent) variables for this study included the following psychometrics: PCL:SV total scale, PCL:SV Part I subscale, PCL:SV Part II subscale, PICTS P composite scale, and PICTS R composite scale. The PICTS P and R scales have item overlap and a resulting interdependency; therefore, regressions with the P and R scales were performed separately.

The third and primary investigation included the demographics which significantly correlated with incident reports (control variables), the PCL:SV and the PICTS P and R composite scales (predictor variables) and their relationship with incident reports (criterion variable). These analyses were investigated using two different models of regression analysis.

The criterion variable was the number of disciplinary infractions received for each inmate after one year of incarceration in the institution where the study took place. Institutional misconduct, as a variable, has received criticism for being too broad a category (Cunningham & Reidy, 1998; Edens, et al., 2001); therefore, instead of using the sweeping category involving a number of incident reports, this variable was disaggregated into aggressive and non-aggressive incident reports. Total incident reports equaled the sum of aggressive and non-aggressive incident reports.

Analyses for Dichotomized Data

Analyses using a dichotomized criterion variable were undertaken using the Statistical Package for Social Sciences 11.0 (SPSS 11.0). The type of correlational analyses between the dichotomized criterion variable and the demographic and predictor variables varied according to the type of data the demographics or predictor variables represented (i.e., continuous or dichotomized). The selection of statistical procedures reflected these differences.

Point Biserial Correlations

Point biserial correlations are used to assess linear relationships between continuous and dichotomized data. In the present study, point biserial correlations were used to assess the relationships between the continuous demographic variables, age and education, and the continuous predictor variables, PCL:SV and PICTS scales, with the dichotomized criterion variable (incident reports received versus not received).

Phi Correlations

Phi Correlations are used for assessing relationships between two dichotomized variables. In this study, martial status (single versus non-single), ethnic status (white versus nonwhite), and offense (aggressive versus non-aggressive) were assessed for significant links with the dichotomized criterion variable (incident reports received versus not received).

ROC Curve Analysis and Classification Table

ROC curve analysis was employed for deriving an area under the curve for predicting accuracy. In doing so, incident reports were dichotomized (received versus not received). In addition to the ROC curve analysis, a classification table was generated in order to assess the predictive accuracy of the psychometric variables. This table included sensitivity, specificity, positive predictive power, negative predictive power, and odds ratios.

Logistic Regression

Logistic regression analysis was employed for assessing incremental validity between the predictor variables and dichotomized criterion variable for predicting incident reports. Logistic regression is a nonparametric version of multiple regression. In logistic regression, several variables are related to a single criterion variable; although these variables can be continuous or categorical, the criterion variable must be categorical (not continuous). In the present study the criterion variable was dichotomized as incident reports received or not received. Logistic regression produces information about how well the obtained frequencies in a particular cell fit the expected frequencies, rather than about how much of the variance each predictor variable accounts for in the criterion.

It is important to consider how variables are ordered for entry in the regression equation. Incremental validity can be assessed with variables entered in three different ways: hierarchically, step-wise, or simultaneously. In step-wise regression, the entry of the variables is computer generated, and is largely not recommended because of the inability to replicate the order (Hunsely & Meyer, 2003). For the current study, the logistic regression analysis used a step-wise or researcher-specified order of entry of the variables. For regression analyses implemented later in this study (for analyzing the criterion variable as count data), simultaneous entry of the variables was used.

Count Data

Many dependent variables are considered *count data* because they represent the occurrence or frequency of an event over a given interval of time. The frequencies of these counts are discrete, nonnegative whole numbers. In the present study the criterion variable, incident reports, is the number of prison infractions received for each inmate over a 12-month period. Because incident report data can be represented as frequencies of occurrence over time, they are considered count data.

If an event such as prison infractions occurs with low frequency, the highest frequency found in the distribution, from the sample will be distributed at zero (indicating the fact that many individuals did not receive an incident report). The rest of the distribution will exhibit decreasing frequency of the event as the value of the count increases. The result is a positively skewed distribution that is characteristic of count data for infrequently occurring events.

Analyzing Count Data

There are several ways to prepare count data for analysis. Common methodological practices include rescaling count data to categories, transforming count data, or using linear or logistic regression for analysis. These commonly used methods, however, raise concerns when they are applied to nonnormal distributions. Researchers have pointed out that using these traditional methods with skewed data can produce misleading results. They have suggested that techniques such as categorizing, transforming the data, and using linear analysis run the risk of wasting information, producing abnormally distributed errors, and/or producing nonsensical negative predicted values (Gardner, Mulvey, & Shaw, 1995; Osgood & Rowe, 1994).

Categorizing data does not violate any assumptions; however, it is subject to cloaking valuable information. For example, if the data included a large range of values, and the range is reduced to a single value or category, the data are less precisely represented because a great deal of information has been lost; as a result, much of the information is wasted (Gardner et al., 1995). Consequently, this lessens statistical power and affects results (Gardner, et al,, 1995).

Transforming data is another commonly used statistical technique, but a technique that draws concern when applied to count data. The transformation of a skewed distribution to a normal distribution is problematic because of the prevalence of zeros (which is characteristic of count data). The heteroscedasticity (non-uniform scatter of plotted data) will produce distorted estimated variances and the modal value will still fall at zero (Gardner, et al., 1995).

Another popular, but suboptimal, means for analyzing count data is with the use of the ordinary least squares model. Walters (2006) found that when using ordinary least squares regression on nonnormal data, the effect of some variables was overestimated and the effect of other variables was underestimated. Thus, applying ordinary least squares regression for analyzing nonnormal data can result in overlooking significant findings (Type II errors) or indicating significance where none exists (Type I error). In contrast to the normal distribution which is continuous both in negative and positive directions; count data are characterized by nonnegative integer values which violate the normality assumption of the ordinary least squares regression. If count data are analyzed as normally distributed data, negative values can be predicted for the non-negative integer data, causing nonsensical predictions.

In place of implementing the traditional statistical methods on nonnormal count data, it is suggested that the Poisson regression model be considered. This regression model has been called the "benchmark" model for count data (e.g., Walters, 2006) and is viewed as a better alternative to the logistic regression model because the latter dichotomizes the dependent variable for analyzing count data (Gardner, et al, 1995; Greene, 2000; Osgood & Rowe, 1990).

The Poisson Regression Model

The use of the Poisson regression model is not frequently found in the social sciences research; it seems to be utilized more often in mathematical statistics and econometrics. In a review of 43 recent studies in criminal psychology that used count data, Walters (2006) found that not a single study implemented the Poisson analysis. Instead the authors of these studies dichotomized the data, treated the data as continuous data (not discrete data), or did both. Reasons have been suggested for this widespread lack in the use of the Poisson regression model; these include a general inattention to the special characteristics of count data (i.e., discrete non-negative integers), ignoring the non-normal distribution, and facing difficulties when trying to apply the Poisson model analysis to social science data (Osgood, 2000; Sturman, 1999; Walters, 2006).

The Poisson distribution has a number of restrictions that can make it impractical in social science research (Walters, 2006). One important restriction of this particular distribution model is that it assumes equivalence of the variance and the mean. That is, randomness is mathematically expressed by the fact that the variance and the mean for the distribution are equal to near-equal. Large differences suggest inequality between the mean and the variance and therefore indicate that the values are not normally distributed. If this equality assumption of the Poisson distribution is violated, then variances will be inconsistently estimated (Osgood & Rowe, 1994).

This assumption of equal variance and mean has been noted as one of the shortcomings of the Poisson distribution model particularly because data from social science research often do not produce equidispersed means and variances. When a significant difference between the mean and the variance exists, the distribution is regarded as being overdispersed. If the Poisson regression model is applied to data that are overdispersed, the standard errors for the predictor values will be underestimated and the findings will be inflated (Gardner et al., 1995; Cameron & Trivedi, 1990). This suggests that the Poisson regression model is a suboptimal choice for analyzing count data that are overdispersed. However, there are modifications of the Poisson model that can be used with an overdispersed Poisson distribution.

Overdispersion and the Negative Binomial Regression Model

The largest area of the distribution of infrequently occurring events is typically at zero, yet a small number of individuals may have extreme counts (e.g., 20), resulting in a positively skewed distribution. Positively skewed distributions may also be overdispersed, and therefore run the risk of violating the equality assumption of the Poisson regression model. When overdispersion is present in count data distributions, the Poisson distribution model is no longer the best choice for analyses. Therefore, positively skewed count data require diagnosis for overdispersion. Cameron and Trivedi's (1990) least squares procedure, for example, is one of a number of ways for detecting overdispersion in skewed count data.

If it is determined that overdispersion in fact exists, a statistical method that is an extension of the Poisson distribution called the negative binomial regression, can be implemented. The negative binomial regression model adds an "overdispersion" parameter to estimate the possible deviation of the variance from that expected under the Poisson. As a result, the negative binomial regression model generates a more conservative estimate of standard errors than the Poisson regression model.

Walters (2006) compared different statistical models for analyzing count data, including the Poisson and the negative binomial regression. The Poisson model overestimated the effect of the variables by underestimating their standard errors. Coefficients generated by the Poisson and the negative binomial regression were roughly equivalent, but the standard errors of the independent variables for the Poisson model were 40% to 300% lower than the standard errors in the negative binomial model.

In a similar study, eight statistical models were compared when analyzing count data. These statistical models included ordinary least squares, ordinary least squares with transformed dependent variable, Tobit, Poisson, overdispersed Poisson, negative binomial regression, ordinal logistic regression, and ordinal probit regression. The Poisson regression model produced more false positives than expected by chance and the negative binomial regression model produced fewer false positives than expected when compared with all the other models (Sturman, 1999).

There are situations in which the use of the Poisson and the negative binomial regression are not indicated for count data. For example, both of these methods do poorly when there is an extreme number of zeros (Greene, 2000). Discerning if the number of zeros is excessive can be achieved by using the diagnostic Vuong statistic (Vuong, 1989). The negative binomial distribution has only recently been applied to the analysis of count data when it is used in the social sciences (Greene, 2000). Future research may indicate other limitations of using this procedure.

Overview of the Analyses in this Study

The analyses used to assess the relationships between and among the variables in this study varied according to whether or not the criterion variable was dichotomized or was represented as count data. In overview, there were three general levels of analyses. First, the preliminary correlational analyses were conducted between each of the demographic variables and incident reports. The second level of the analyses investigated the relationships between each of the psychometric variables and incident reports (total, aggressive, and non-aggressive).Two statistical models were implemented for each analysis for these two levels of this study. Correlational analyses that were used in the preliminary and second levels of the present study were conducted first by implementing the ordinary least squares model (for dichotomized data); they were then analyzed using the negative binomial univariate regression (for count data).

The third level of the study was the primary investigation; to determine if there was incremental validity between the psychometric variables and control variables for predicting incident reports. The logistic regression analysis and the negative binomial regression analysis models were implemented for this part of the investigation, just as they were in the previous two levels of analyses. Logistic regression analysis was used for analyzing dichotomized data and the negative binomial regression analysis was used for analyzing count data.

Steps were taken to assess for overdispersion in the Poisson distributions for count data. Cameron and Trivedi's (1990) least squares procedure was implemented to assess for overdispersion in each of the regression equations. This procedure is a simple t test of whether or not the coefficient is significantly different from zero. If the variance of the regression significantly exceeded the mean, overdispersion was present. In sum, there were 36 analyses investigated both as dichotomized data and as count data.

CHAPTER 4

RESULTS

This chapter reviews the descriptive statistics for the demographic, predictor, and criterion variables. This is followed by an overview of the analyses and then by an itemized review of the eight hypotheses. Tables are included for further clarification and understanding.

Descriptive Statistics for the Participants

Age

Participants ranged in age from 18 to 65 years. The mean age was 34.3 years with a standard deviation of 8.6.

Education Level

Years of education were defined as the last year of school completed. Completion of a GED was considered 12 years. The years of education ranged from 5 to 18 years, with a mean of 11.12 and standard deviation of 1.86 in this sample.

Ethnic Status

The distribution of participants by ethnic status is presented in Table 2. Approximately 20% of the participants were white. The 80% nonwhite participants included African American, Hispanic, and ‘other’ (Asian in this study).

Table 2

Frequency Distribution of Ethnic Status

Ethnic Status	Number	Percentage
Caucasian	29	19.9%
African American	79	54.1%
Hispanic	37	25.3%
Other	1	0.7%

Marital Status

Nearly three-fourths (73.3%) of the participants were not married (single, divorced or widowed), and a little more than one quarter (26.7%) were married. The frequency distribution of marital status is presented in Table 3.

Table 3

Frequency Distribution of Marital Status

Marital Status	Number	Percentage
Single	73	50.0%
Married	39	26.7%
Divorced	33	22.6%
Widowed	1	0.7%

Confining Offense

The confining offense is the offense that was committed and for which the inmate was incarcerated. Over a quarter (29.4 %) had aggressive confining offenses (violent or robbery) and nearly three quarters (70.6%) had confining offenses regarded as non-aggressive (property, drugs, firearms, and miscellaneous non-aggressive offenses). A frequency distribution of the participants' confining offenses is listed in Table 4.

Descriptive Statistics for the Psychometric Variables

PCL:SV

A score of 18 or greater is indicative of psychopathy on the PCL:SV. In this sample 23 (15.8%) inmates scored above the cutting score and 123 (84.2%) fell below the cutting score. The means, standard deviations, and ranges for the PCL:SV are shown in Table 5.

Table 4

Frequency Distribution of Participants by Confining Offense

Confining Offense	Number	Percentage
Violent	17	11.6%
Robbery	26	17.8%
Property	3	2.1%
Drug	67	45.9%
Firearms	17	11.6%
Other	16	11.0%

Table 5

Descriptives of the PCL:SV

PCL:SV Score	Mean	Standard Deviation	Range
Total	13.49	4.34	3 - 23
Part I	5.58	2.64	0 - 12
Part II	7.80	2.45	2 - 12

PICTS P and R Subscales

The PICTS P and R composite subscales have a standard cutting score of 60, although sometimes a stricter cutting score of 55 is used. Individuals falling above the P cutting score are viewed as having adopted a proactive style of criminal thinking; those below the cutting score have not. Similarly, individuals scoring above the R cutting score are regarded as having adopted a reactive style of criminal thinking; those below the cutting score do not exhibit this characteristic pattern. Tables 6 and 7 present the descriptives for these variables.

Table 6

Descriptives of the PICTS P and R Scales

PICTS Scales	Mean	Standard Deviation	Range
P	71.79	22.23	43 – 145.5
R	71.69	23.24	44 – 129

Table 7

Descriptives of the PICTS P and R Cutting Scores

Cutting Scores for the P and R Scales		N (Percentage)	
		Above	Below
PICTS P Scale	55	47 (32.3%)	99 (67.8%)
	60	31 (21.2%)	115 (78.8%)
PICTS R Scale	55	44 (30.1%)	102 (69.9%)
	60	22 (15.1%)	124 (84.9%)

Descriptives of the Criterion Variable

Over the 12 month follow up, there were a total of 109 incident reports which were committed by 51 (34.9%) inmates. That is, 95 (65%) inmates received no incident reports over the 12 month follow up. Of the 109 incident reports, 91 (83.5%) were non-aggressive incidents and 18 (16.5%) were aggressive incidents. The total number of incident reports per inmate ranged from 0 to 20, with a mean of .75 and a standard deviation of 1.96. Over the 12 month period, single infractions were committed by 27 (18.5%) inmates; a total of two infractions were committed by 16 (11%) inmates; and total of three or more infractions were committed by 8 (5.5 %) inmates. The mean, standard deviation, and range for total, aggressive, and non-aggressive incident reports are shown in Table 8, and the frequency distribution for incident reports is shown in Table 9.

Overview of the Analyses

Two statistical computer packages were used to analyze the data for this study. One package, SPSS version 11.0 addressed the criterion variable as dichotomized data, and the LIMDEP version 8.0, an econometrics package, addressed the criterion variable as count data.

Table 8

Descriptives of Incident Reports

Incident Reports	Mean	Standard Deviation	Range
Total	.75	1.96	0 - 20
Aggressive	.12	.79	0 - 9
Non-aggressive	.62	1.40	0 - 11

Table 9

Frequency Distribution of Inmates and Incident Reports

Number of Incident Reports	Total Incident Reports N (Percentage)	Aggressive Incident Reports N (Percentage)	Non-aggressive Incident Reports N (Percentage)
1	27 (18.5)	7 (4.8)	25 (17.1)
2	16 (11.0)	1 (.7)	14 (9.6)
3	4 (2.7)	__	3 (2.1)
5	1 (.7)	__	1 (.7)
6	__	__	1 (.7)
7	1 (.7)	__	1 (.7)
9	1 (.7)	1 (.7)	__
11	__	__	1 (.7)
20	1 (.7)	__	__

Dichotomizing the dependent variable offered the opportunity to explore the data in the traditional manner (i.e., ROC analysis, classification analysis, logistic regression). However, it is argued that when count data are analyzed in traditional ways spurious significant results may result (Cameron & Trivedi, 1990). Therefore an alternative analysis was implemented in this study; the negative binomial regression model was used to investigate the hypotheses when the criterion variable was denoted as the count of incident reports.

The statistical analyses for the hypotheses required a variety of correlational methods to assess the relationships between the variables. **Point biserial** correlations were used to investigate age and education with the dichotomized criterion measure (incident reports) (Hypotheses 1, 2). **Phi correlation** coefficients were employed for assessing correlations between dichotomized control variables (ethnic status, marital status, and confining offense) and the dichotomized criteria (Hypotheses 3, 4, 5). **Negative binomial univariate regressions** were conducted on all the demographic variables using count criterion variable data (Hypotheses 1, 2, 3, 4, 5). **Logistic regression** and **negative binomial univariate regression** were used to asses the relationships between the predictor variables and the count criterion variable data (Hypothesis 6, 7). A **ROC curve analysis** and a **classification table** were derived to assess predictive accuracy of the psychometric variables (Hypothesis 7). **Logistic regression** and **negative binomial multivariate regression** were employed to investigate incremental validity between the predictor and criterion variables as dichotomized and count data, respectively (Hypothesis 8).

Hypotheses and Specific Findings

Hypothesis #1

Hypothesis 1 predicted that age would be inversely related to number of incident reports. Because age is a continuous variable and incident reports were dichotomized, a point-biserial correlation was used for this investigation. Incident reports were dichotomized as 0 = none received and 1 = some received. When one variable is continuous and the other is dichotomous, a Pearson product moment correlation can be used, but since one variable is dichotomized, the correlation is called point-biserial to designate the type of variables in the correlation.

The inverse relationship that was hypothesized was confirmed for the three categories of incident report: r_{pb} = -.25, p < .01, r^2 = .06, two-tailed, for total incident reports; r_{pb} = -.21, p < .05, r^2 = .04, two-tailed, for aggressive incident reports, and; r^2= -.22, p < .05, r^2 = .05, two-tailed, for non-aggressive incident reports. Table 10 presents the results and illustrates coefficients of determination, which indicate that 6%, 4%, and 5% of the variances in the respective incident reports were attributable to age.

When the incident reports were subsequently analyzed as count data, the negative binomial regression demonstrated similar results: age was significantly correlated with incident reports. Findings for total incident reports were t = -4.04, p < .001; for aggressive incident reports t = -2.55, p < .05; and non-aggressive incident

Table 10

Correlations for Demographic and Criterion Measures

	Correlations		
Control Variable	IRd-T	IRd-A	IRd-N
Age	-.25**	-.21*	-.22*
Education	-.10	-.03	-.09
Ethnic Status	.08	-.02	.12
Marital Status	.08	-.08	-.10
Offense	.06	-.02	.08

Note. IRd-T = dichotomized measure of total incidents; IRd-A = dichotomized measure of aggressive incidents; IRd-N = dichotomized measure of non-aggressive incidents; ethnic status dichotomized as white (0) versus nonwhite (1); marital status dichotomized as single (0) versus non-single (1); offense dichotomized as aggressive (0) versus non-aggressive (1); age and education correlations are point biserial coefficients and ethnic, marital, and offense correlations are phi correlations.

*p < .05. **p < .01.

reports *t* = -3.43, p < .01. See Table 11 for the results. In this study younger inmates received more total incident reports, more aggressive incident reports, and more non-aggressive incident reports than did older inmates. Thus this hypothesis was confirmed.

Hypothesis #2

It was hypothesized that education would have an inverse relationship with disciplinary infractions: the lower the level of education, the higher the number of incident reports. A point biserial correlation was used because education level is continuous and incident reports were dichotomized (0 = none received versus 1 = received). When incident reports were analyzed as count data, the negative binomial regression was used. For both point biserial and negative binomial regression statistical models, education was not significantly related to total, aggressive, or non-aggressive incident reports. Although there was an overall negative trend to the correlation these analyses do not confirm this hypothesis. Tables 10 and 11 depict the results of the dichotomized and count data respectively for Hypothesis 2. Because education was not a demographic variable significantly related to incident reports it was not carried over as a control variable in the primary incremental regression analyses.

Table 11

Negative Binomial Regression Evaluations Between Demographic and Criterion Measures

	IRc-T			IRc-A			IRc-N		
Variable	Coeff	SE	t	Coeff	SE	t	Coeff	SE	t
Age	-0.0870	.0215	-4.04***	-0.2236	.0876	-2.55*	-0.0745	.0217	-3.43***
Education	-0.1285	.0870	-1.48	-0.0033	.2273	-.02	-0.1534	.0891	-1.72
Ethnic Status	1.0130	.4737	2.14*	0.6846	1.1723	.58	1.0900	.5044	2.16*
Marital Status	-0.6657	.3268	-2.04*	-1.6094	.8969	-1.79	-0.5167	.3368	-1.53
Offense	0.3384	.3696	0.92	0.7359	1.0055	.73	0.2695	.3788	.71

Note. Each evaluation was analyzed separately. IRc-T = total incident reports (count data); IRc-A = aggressive incident reports (count data); IRc-N = non-aggressive incident reports (count data); Coeff = b coefficient: SE = standard error; t = b/SE.

*p < .05. ***p< .001.

Hypothesis #3

Hypothesis 3 proposed that ethnic status would be correlated with incident reports. More specifically, it was hypothesized that non-white inmates would receive significantly more incident reports than white inmates. A phi correlation was used because both variables were dichotomized. Ethnic status was dichotomized, 1 = white versus 2 = nonwhite, and incident reports were dichotomized as 0 = none received and 1 = some received. This correlation failed to produce significant findings. Table 10 shows these findings.

When subsequently analyzing incident reports as count data via the negative binomial regression, the findings were different from the results from the ordinary least squares correlations. Ethnic status was found to be significantly related to total incident reports, $t = 2.14$, $p < .05$ and non-aggressive incident reports, $t = 2.16$, $p < .05$. That is, non-white inmates received more total and non-aggressive incident reports than did white inmates. See Table 11 for a review of these findings.

Hypothesis #4

It was hypothesized that marital status would be correlated with incident reports in which single inmates would have more incident reports than non-single inmates. A phi coefficient was used to assess marital status and incident reports because both variables were dichotomized. Marital status was dichotomized as single (1) or non-single (2) and the dependent variable, incident reports, was dichotomized either as none received (0) or as some received (1) for total, aggressive, and non-aggressive incident reports. Table 10 illustrates that these dichotomized variables produced no significant correlations.

By contrast, the negative binomial regression analyses of the same data produced a significant finding: Marital status was related to total incident reports, $t = -2.04$, $p < .05$. Single inmates received more total incident reports than did non-single inmates. See Table 11 for these findings.

Hypothesis #5

It was hypothesized that the type of confining offense would be related to incident reports. Inmates with violent confining offenses were expected to have more incident reports than inmates with non-violent confining offenses. A phi coefficient was used to analyze the relationship between the two dichotomous variables. Confining offense was categorized as violent (1) or nonviolent (2), and incident reports were dichotomized as none received (0) or some received (1). As shown in Table 10, no significant correlations were found with this analysis.

When the variables were analyzed using the negative binomial regression, parallel findings surfaced: no significance was found. Table 11indicates this finding. Confining offense was not a demographic variable that was significantly related to incident reports; consequently, it was not considered as a control variable in the primary regressions.

Hypothesis #6

It was predicted that the PCL:SV psychometric variables, total, Part I, and Part II would demonstrate significant positive correlations with incident reports (total, aggressive, and non-aggressive). To assess this hypothesis, point biserial correlations were conducted with incident reports dichotomized as not received (0) or received (1). As denoted in Table 12, no significant findings surfaced for any of the three PCL:SV scores.

However, when the PCL:SV Total, Part I, and Part 2 scores were used in negative binomial univariate regression, Part I indicated no significance with incident reports, but Part II was significant for total, aggressive, and non-aggressive incident reports and PCL:SV total was significantly related to total and aggressive incident reports. Table 13 shows these details.

Hypothesis #7

It was predicted that the psychometric variables, PICTS P and R scales would demonstrate significant positive correlations with incident reports (total, aggressive, non-aggressive).

To assess the relationships between the psychometrics and incident reports, two point biserial correlations were conducted on the three categories of incident reports, with incident reports dichotomized as not received (0) or received (1). As Table 12 indicates, a significant correlation showed up between the PICTS P scale and aggressive incident

Table 12

Zero-Order Point-Biserial Correlations Between Predictor Variables and Criterion Measures

	IRd-T	IRd-A	IRd-N
PCL:SV Total	.04	.15	.04
PCL:SV Part I	-.01	.11	-.02
PCL:SV Part II	.07	.16	.07
PICTS P Scale	.07	.23**	.06
PICTS R Scale	.12	.15	.11

Note. IRd-T = dichotomized measure of total incidents; IRd-A = dichotomized measure of aggressive incidents; IRd-N = dichotomized measure of non-aggressive incidents.

**p<.01.

Table 13

Negative Binomial Regression Evaluations Between Psychometric and Criterion Variables

	IRc-T			IRc-A			IRc-N		
Variable	Coeff	SE	t	Coeff	SE	t	Coeff	SE	t
PCL:SV Total	.0826	.0390	2.11*	.2518	.1071	2.35*	.0543	.0410	1.32
PCL:SV Part I	.0171	.0700	0.25	.2637	.2232	1.18	-.0170	.0708	-2.41
PCL:SV Part II	.1830	.0639	2.86**	.4628	.1780	2.60**	.1414	.0675	2.09*
PICTS P	.0207	.0063	3.25**	.0544	.0154	3.53***	.0151	.0068	2.21*
PICTS R	.0212	.0072	2.94**	.0487	.0194	2.50*	.0166	.0075	2.21*

Note. Each evaluation was analyzed separately. IRc-T = total incident reports (count data); IRc-A = aggressive incident reports (count data); IRc-N = non-aggressive incident reports (count data); Coeff = b coefficient; SE = standard error; *t* = b/SE.

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

reports (r_{pb} = .23, p < .01, r^2 = .05, two tailed). The PICTS P was correlated with aggressive incident reports, with 5% of the variability of the criterion accounted for by the PICTS P composite scale.

When these variables were assessed by the univariate negative binomial regression method, additional significant findings surfaced beyond that found in the logistic regression anaysis. Both PICTS P and R scales were significantly associated with total, aggressive, and non-aggressive incident reports. Table 13 shows these details.

ROC

The ROC analysis and the Area Under the Curve (AUC) calculations were used to provide an index of predictive accuracy for the criterion variables. The ROC curve analysis uses each point on the measure to determine the AUC for the psychometrics at various cutoff points for the 95% confidence interval. An AUC = 1.0 indicates perfect accuracy; AUC = 0.0 indicates a perfect inverse relationship, and an AUC = .5 indicates little to no predictive accuracy for that psychometric.

Table 14 illustrates one significant finding: The PICTS P scale produced an AUC = .74 (p = < .05) in predicting aggressive incident reports. This puts the PICTS P in the average range for predictive ability. Figure 1 shows this ROC curve analysis.

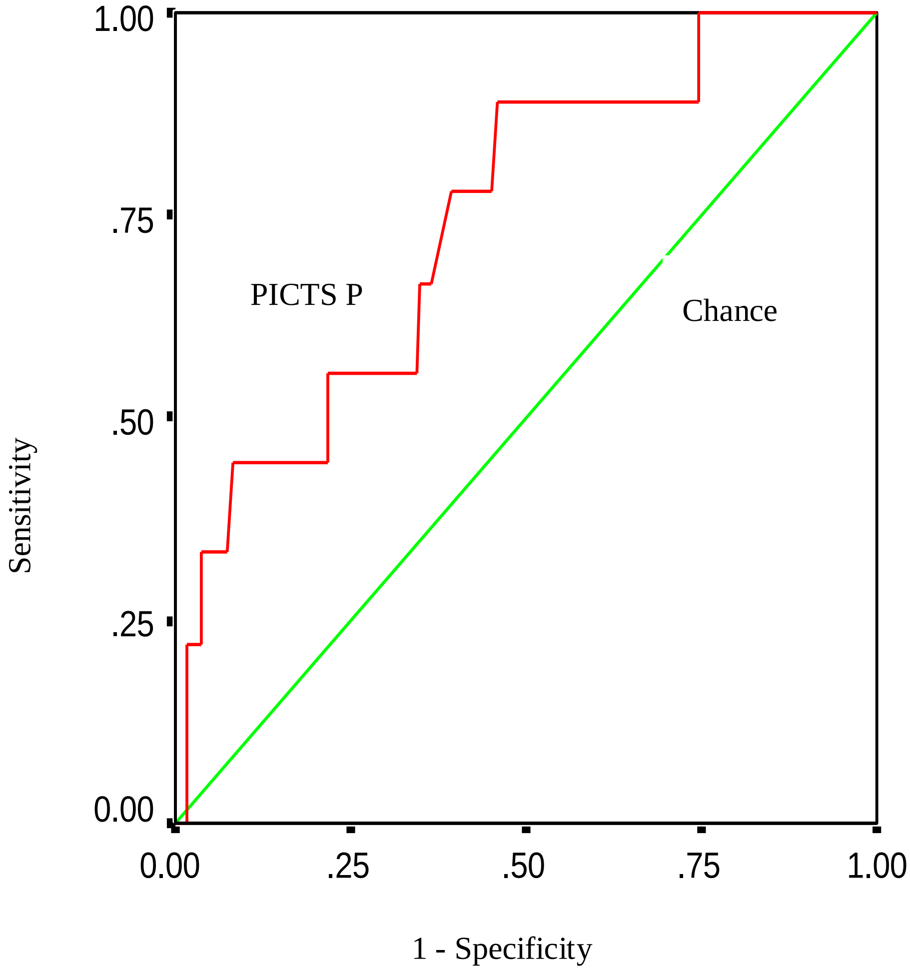
Table 14

Area Under the Curve for Predictor Variables with Respect to Incident Reports

	IRd-T			IRd-A			IRd-N		
Variable	AUC	SE	95% CI	AUC	SE	95% CI	AUC	SE	95% CI
PCL:SV T	.511	.049	.415 - .607	.674	.089	.500 - .848	.514	.050	.415 - .613
PCL:SV Pt. I	.507	.049	.411 - .603	.618	.086	.449 - .788	.510	.050	.412 - .608
PCL:SV Pt. II	.531	.051	.430 - .631	.687	.100	.492 - .882	.052	.490	.430 - .638
PICTS P	.546	.050	.447 - .645	.746*	.082	.585 - .906	.053	.506	.433 - .638
PICTS R	.587	.048	.492 - .681	.691	.077	.540 - .843	.577	.050	.479 - .675

Note. IRd-T = dichotomous measure of total incident reports; IRd-A = dichotomous measure of aggressive incident; IRd-N = dichotomous measure of non-aggressive incident reports; PCL:SV T = PCL:SV total score; PCL:SV Pt. I = PCL:SV Part I score; PCL:SV Pt. II = PCL:SV Part II score; PICTS P = proactive scale score; PICTS R = PICTS reactive scale score; AUC = Area under the curve; SE = standard error; CI = 95th % confidence for the AUC.

Figure 1.



ROC curve for PICTS P subscale with respect to aggressive incident reports

Classification Analysis

Classification is a means of putting offenders into discrete categories or classes for decision-making purposes. Classification in a statistical sense is grouping these individuals so that that the variance within groups is less than the total variance (Sechrest, 1987). In prisons, the most common type of classification is based upon risk level (Andrews & Bonta, 2003). For the present study, a summary of classification accuracy for predicting risk is found in Table 15.

Classification analysis explored the PICTS P and R scales at two different cutting scores, a T-score of 55 and a T-score of 60, and the PCL:SV with a single cutting score of 18. As the results indicate, the PICTS P, PICTS R, and PCL:SV total scales produced a trend toward greater specificity than sensitivity for incident reports (total, aggressive, and non-aggressive). Additionally, there was higher negative predictive power (the probability that incident reports were not present when the test scores were below the cutting score) than positive predictive power (the probability that incident reports were present when the test scores were above the cutting score) in this sample of inmates.

Odds Ratios. The odds ratios offer another means for analyzing the accuracy of a test. Odds ratios in this study represent the odds of incident reports occurring. For example, as Table 15 indicates, inmates who scored above the cutting score of 60 on the PICTS R for aggressive incident reports are three times more likely than those scoring below the cutting score to receive aggressive incident reports. Overall none of the odds ratios indicated significance when using the standard of the lower end of the confidence interval not being greater than one.

Table 15

Classification Results Using Two Cutting Score for the PICTS P and R Scales

	Outcome	CS	SN	SP	PPP	NPP	OR	95%CI
PICTS P	IRd-T	55	. 33	.68	.36	.66	1.08	.53 – 2.23
		60	.20	. 78	.32	.64	.86	.37 - 1.99
	IRd-N	55	.35	. 69	.34	.70	1.19	.57 – 2.48
		60	.20	. 78	.29	.68	.86	.36 – 2.05
	IRd-A	55	.56	. 69	.11	.96	2.83	.72 – 11.06
		60	.44	. 80	.13	.96	3.26	.82 – 12.96
PICTS R	IRd-T	55	.31	. 71	.36	.66	1.94	.52 – 2.28
		60	.18	. 86	.41	.66	1.35	.54 – 3.41
	IRd-N	55	.33	. 71	.34	.70	1.19	.56 – 2.51
		60	.20	. 87	.41	.71	1.63	.64 – 4.13
	IRd-A	55	.44	. 71	.10	.95	1.94	.50 – 7.59
		60	.33	. 86	.14	.95	3.11	.72 – 13.48
PCL:SV	IRd-T	18	.14	. 83	.30	.64	.77	.30 – 2.05
	IRd-N	18	.15	. 84	.30	.68	.94	.36 – 2.47
	IRd-A	18	.33	. 85	.13	.92	2.93	.68 – 12.65

Note: IRd-T = dichotomous measure of total incident reports, IRd-N = dichotomous measure of non-aggressive incident reports; IRd-A = dichotomous measure of aggressive incident reports; CS = cutting score, proportions of the sample at or above the cutoff were PICTS P (55) = 32.2%, PICTS P (60) = 21.2 %; PICTS R (55) = 30.1%; PICTS (60) = 15.1; PCL:SV (18) = 15.8%; SN = sensitivity; SP = specificity; PPP = positive predictive power; NPP = negative predictive power; OR = odds ratio; 95% CI = 95th % confidence interval for the odds ratio; N = 146.

Hypothesis #8

Hypothesis 8, the primary investigation in this study, stated that the PICTS R scale would achieve incremental validity relative to the PCL:SV total in predicting incident reports. This hypothesis was investigated initially using logistic regression analysis for exploring the criterion variable as dichotomized data. The investigation then implemented the negative binomial regression model for analyzing the same criterion variable but as count data.

Dichotomized Data Analysis

To investigate Hypothesis 8 with the logistic regression analysis, incremental validity was assessed by entering the demographic variables age, ethnic status, marital status and the predictor variable, PCL:SV, in the first block of the regression analysis. Because confining offense and education level failed to show significance in the preliminary analyses these demographics were not included in this analysis. The PICTS P and then R scale scores were added as the second block with regard to the dependent variable (which was total, aggressive, and non-aggressive incident reports). Thus, there were six logistic regressions performed on the data; 146 cases were analyzed for each of the regressions. In the end, none of the logistic regressions indicated significant incremental validity when the criterion variable was dichotomized.

Count Data Analysis

Next, incident reports were analyzed using the negative binomial regression. Six main regressions, utilizing 146 cases for each regression were performed. Because the PICTS P and PICTS R have item overlap they were analyzed using separate equations for the three categories of incident reports. Thus, there were six primary regression analyses.

Testing for overdispersion with count data. Each of the six main regressions investigated for incremental validity were initially tested for overdispersion. Cameron and Trivedi's (1990) least squares *t* test was used for assessing this overdispersion of the total, aggressive, and non-aggressive incident reports distributions. The results are shown in Table 16, indicating all six regression equations were significantly overdispersed.

Table 16

T_{opt} Test Results for Overdispersion

Multivariate Combination	t_{opt}
PICTS P and PCL:SV Total on IR-T	3.63***
PICTS R and PCL:SV T on IR-T	3.68***
PICTS P and PCL:SV Total on IR-A	7.43***
PICTS R and PCL:SV T on IR-A	4.85***
PICTS P and PCL:SV T on IR-N	2.74**
PICTS R and PCL:SV T on IR-N	2.77**

Note. IR-T = Total Incident Reports; IR-A = Aggressive Incident Reports; IR-N = Non-Aggressive Incident Reports.

** $p < .01$. *** $p < .001$.

Negative binomial regressions. The six primary regressions were analyzed using LIMDEP, a software program that enters the variables of each equation simultaneously rather than sequentially. Variables showing significance within an equation have incremental validity relative to the other variables in the equation.

The first two regression equations investigated incremental validity among the predictor and control variables for total incident reports. These two equations were similar in all respects except that the PICTS P was used in the first equation and the PICTS R was used in the second equation. The predictor variables in both equations were the PCL:SV total and either the PICTS P or R composite scale.

The control variables in both of these equations were age, ethnic status, and marital status. The equation that included the PICTS P indicated no significant incremental validity between the psychometrics; however, the control variable age demonstrated significance, indicating age adds incremental validity to all the other variables in this equation. Table 17 presents these findings.

The second equation for assessing incremental validity for total incident reports included the PICTS R, the PCL:SV total, age, ethnic status, and marital status. Significance was demonstrated between the two psychometrics PICTS R and the PCL:SV, as well as with one control variable, age. These three variables provided significant incremental validity relative to each other and to the other variables in this equation. See Table 17 for these findings.

The next two regressions investigated incremental validity among the variables for aggressive incident reports. These two equations were identical with the exception that

Table 17

Negative Binomial Regression Results for Total Incident Reports

	PICTS P			PICTS R		
Variable	Coeff	SE	t	Coeff	SE	t
Constant	-0.6554	1.3675	-0.47	-0.9960	1.3663	-0.72
Age	-0.0751	0.0233	-3.22***	-0.8322	0.0229	-3.62***
Ethnic St	0.4907	0.4587	1.07	0.4763	0.4579	1.04
Marriage	0.0549	0.3260	0.16	0.0549	0.3260	0.16
PCL:SV T	0.0715	0.0367	1.94	0.0774	0.0355	2.17*
P	0.0092	0.0065	1.41			
R				0.0152	0.0065	2.32*

Note. Ethnic St. = Ethnic Status; PCL:SV T = PCL:SV Total; P = PICTS P; R = PICTS R; Coeff = b coefficient; SE = standard error; *t* = b/SE.

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

one contained the PICTS P and the other contained the PICTS R. Thus this second set of equations included either the PICTS P or PICTS R, the PCL:SV, and the control variable, age.

Variables in the equation that included the PICTS P demonstrated significance: both the PICTS P and age demonstrated incremental validity. The results are shown on Table 18.

The equation for aggressive incident reports that included the PICTS R showed significant incremental validity for age and for the PCL:SV. The results are shown in Table 18. Age and the PCL:SV indicated significant incremental validity relative to each other and to PICTS R. That is, PICTS R did not have significant incremental validity to age and the PCL:SV for this equation. These results are shown in Table 18.

For non-aggressive incident reports, the last two equations included the PCL:SV, the PICTS P or PICTS R, and the control variables, age and ethnic status. As shown in Table 19, the equation containing the PICTS P showed one significant finding, which was for age. Thus, age adds incremental validity to the other variables in the equation. In the equation for non-aggressive incident reports that included the PLC:SV, the PICTS R, and the control variables, age and ethnic status had the identical finding: Age was the only variable significantly providing incremental validity to the other variables. This is indicated in Table 19.

Table 18

Negative Binomial Regression Results for Aggressive Incident Reports

	PICTS P			PICTS R		
Variable	Coeff	SE	t	Coeff	SE	t
Constant	-3.3998	2.6040	-1.306	-2.4950	2.6595	-0.938
Age	-0.1454	0.0640	-2.271*	-0.1807	0.0671	-2.693**
PCL:SV	0.1636	0.0879	1.861	0.2107	0.0894	2.356*
P	0.0354	0.0147	2.405**			
R				0.0304	0.0156	1.947

Note. PCL:SV = PCL:SV Total; P = PICTS P; R = PICTS R; Coeff = b coefficient; SE = standard error; *t* = b/SE.

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

Table 19

Negative binomial regression Results for Non-aggressive Incident Reports

	PICTS P			PICTS R		
Variable	Coeff	SE	t	Coeff	SE	t
Constant	-0.8288	1.4290	-0.58	-1.1953	1.4215	-0.84
Age	-0.0656	0.0226	-2.90**	-0.0686	0.0217	-3.15**
Ethnic St	0.6874	0.5024	1.36	0.6350	0.4998	1.27
PCL:SV	0.0560	0.0391	1.43	0.0579	0.0381	1.52
P	0.0049	0.0069	0.71			
R				0.0120	0.0068	1.75

Note. Ethnic St. = Ethnic Status; PCL:SV = PCL:SV Total; P = PICTS P; R = PICTS R; Coeff = b coefficient; SE = standard error; *t* = b/SE.

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

Supplemental

Supplemental analyses were conducted using both logistic and negative binomial regressions in order to better understand the roles that the PCL:SV, Part I and Part II have in relation to one another and to incident reports. The first part of this supplemental analysis investigated Part I and Part II alone, without demographic variables added into the incremental validity equation. Logistic regressions were employed for pitting Part I against Part II for dichotomized total, aggressive, and non-aggressive incident reports. The results indicated no significant incremental validity relative to each other.

The same equations were then analyzed by the negative binomial regression analysis with incident reports represented as count data. When Part I and Part II were pitted against each other with no other variables present in the equation, Part II added significant incremental validity to Part I for total, aggressive, and non-aggressive incident reports. By contrast, Part I did not show incremental validity relative to Part II. See Table 20 for these results.

Because incremental validity was found between Part I and Part II, an additional assessment was executed. The next part of the supplemental analysis assessed Part I and Part II along with the same demographic variables that were used in the main analyses for total, aggressive, and non-aggressive incident reports. Thus, for total incident reports, the equation included Parts I and II, age, ethnic status, and marital status. The equation for aggressive incident reports included Parts I and II and age, and the

Table 20

Negative Binomial Regression Results for PCL:SV Part I and Part II

	IRc-T			IRc-A			IRc-N		
Variable	Coeff	SE	t	Coeff	SE	t	Coeff	SE	t
Constant	-.0907	.9535	-0.10	-6.3930	1.7830	-3.56*	-1.4390	0.5984	-2.41
Part I	-.0775	.0728	-1.07	0.0070	0.2030	0.97	0.0904	0.0747	-1.21
Part II	.2143	.0704	3.04**	0.4596	0.1960	2.34*	0.1777	0.0740	2.40*

Note. IRc-T = total incident reports (count data); IRc-A = aggressive incident reports (count data); IRc-N = non-aggressive incident reports (count data); Coeff = b coefficient: SE = standard error; t = b/SE.

*p < .05. **p < .01.

equation for non-aggressive incident reports included Parts I and II, age, and ethnic status.

The negative binomial regression analyses indicated that when these demographic variables were included in the regressions, Part II no longer added significant incremental validity relative to the other variables or to Part I.

CHAPTER 5

DISCUSSION

This chapter summarizes the present study, reviews the relevant findings, and discusses the implications of the results in light of the existing literature including their contribution to the field. Possible limitations of the study are discussed along with recommendation for future research.

Relevant Findings

Preliminary Analyses (Demographics)

Participants ranged in age from 18 to 65 years. The mean age was 34.3 years with a standard deviation of 8.6. Years of education ranged from 5 to 18 with a mean of 11.2 and a standard deviation of 1.86. The ethnic status included nearly 20% white and 80% nonwhite inmates. Regarding marital status, 73.3% of inmates were not married and 26.7% were married. Confining offense data indicated that 29.4% of the participants were incarcerated for aggressive acts and 71.6% for non-aggressive acts. In sum, the "average" participant was 34.3 years old, attended school for 11.2 years, and was more likely to be non-white, not married, and incarcerated for a non-aggressive crime.

Over the12 month follow up period there were 109 incident reports committed by 35% of the inmates. This suggests that more than one in three inmates received an incident report. When the 109 incident reports were disaggregated, 83.5% (n=91) were non-aggressive and 16.5% (n=18) were aggressive. The base rate for receiving a non-aggressive incident report was 31.5%; the rate for receiving an aggressive incident report was 6.2%. These base rates indicate that there was a 31.5% chance that the occurrence of an infraction would be non-aggressive and a 6.2% chance that the occurrence of an infraction would be aggressive.

The mean number of infractions for the selected sample was 3.2 over a 12 month period. In the present study 94 % of inmates never received serious (aggressive) violations and a small portion of inmates (5.5%) were responsible for nearly half of all incident reports.

The recommended cutting score for the PCL:SV is 18; scores equal to or greater than 18 indicate psychopathy (Hart, et al., 1995). In this study nearly 16% (n=23) of the scores were above the cut off. The PICTS uses two cutting scores, 55 and 60. About one third of the inmates scored above the cutting score of 55 for each of the ideation types (proactive and reactive). Nearly one fifth of the inmates scored above the cutting score of 60 for each of the ideation types (proactive and reactive).

The negative binomial univariate regression indicated that age, ethnic status, and marital status had significant correlations with total incident reports. That is, younger, non-white, single inmates were more likely to have received one or more incident reports than older, white, married inmates. Age was the only significant variable associated with aggressive incident reports. Younger inmates had significantly more aggressive incident reports when compared with older inmates. Age and ethnic status were significantly associated with non-aggressive incident reports, indicating that younger non-white inmates had significantly more non-aggressive incidents. The other variables, which were education and confining offense, showed no significant relationship with the criterion variable. Only those demographics demonstrating significant relationships with the criterion variables were employed in the primary regression analyses as control variables.

Analyses of Psychometric Variables

The analyses that preceded the primary investigation included a review of the relationship between the demographics and incident reports, and between psychometric variables and incident reports. These findings suggested that higher scores on the PCL:SV total scale were significantly associated with older inmates imprisoned for aggressive confining offenses. Part I scores of the PCL:SV were significantly associated with older, married inmates incarcerated for aggressive confining offenses. The PICTS P composite scale was significantly related to younger, non-white inmates.

Subscales from the two psychometric instruments were examined for significant relationships with incident reports. These subscales included the PCL:SV total, Parts I and II scores, and the PICTS P and R scores. These psychometrics correlated with incident reports (total, aggressive, and non-aggressive) with two exceptions. The PCL:SV total scores were significantly correlated with total and aggressive incident reports but were not significantly related to non-aggressive incident reports. The other exception was that Part I of the PCL:SV indicated no significant relationships with incident reports (total, aggressive, or non-aggressive).

In a supplemental analysis between PCL:SV Parts I and II, Part II added significant incremental validity beyond Part I for the total, aggressive, and non-aggressive incident reports. However, when demographic variables (age, ethnic status, and marital status) were included in subsequent regressions, Part II no longer added significant incremental validity relative to Part I or any of the other control variables.

Predictive Accuracy of the Psychometric Variables

When the psychometric variables and incident reports were analyzed for relationships and subsequent classification results, one significant finding surfaced: The PICTS P correlated with aggressive incident reports, accounting for 5% of the variance. Similarly, when the psychometric variables and incident reports were entered into a ROC curve analysis, only the PICTS P composite scale achieved significance. The PICTS P composite scale evidenced an AUC of .75 as a predictor of aggressive incident reports. This means there is a 75% chance that an inmate with a high P score at the 60 cutoff would receive aggressive incident reports.

The standard indices computed for predictive accuracy included sensitivity, specificity, positive predictive power, and negative predictive. The strongest indices for the PCL:SV were compared with the base rates for aggressive incidents. In this study the base rate of aggressive incident reports was 6.2%. The PICTS P, using 55 as the cut off, could accurately identify 56% of the true positives and 69% of the true negatives. In conclusion the PICTS P was not as successful a predictor as simply predicting the chance of non-aggressive behavior, which would be correct 93.8% of the time. The strongest PICTS R finding was for aggressive incident reports using a cut off of 60. The PICTS R was able to identify accurately 33% of the true positives and 86% of the true negatives. Relative to the accuracy of the PCL:SV total, its strongest association was with aggressive incident reports which was similar to the PICTS R prediction, accurately identifying 33% of the true positives and 85% of the true negatives.

Incremental Validity

The third and primary analyses of the study investigated incremental validity of the PICTS R score relative to the PCL:SV total score. The demographics that produced significant relationships with the criterion measures were included in the regression equations as control variables. The PICTS P scale was also included for the purpose of investigative speculation. Because the PICTS P and R scales have overlap they were used separately in each of the regression equations. Thus, the six main regressions were:

For total incident reports:

1. Age, ethnic status, marital status, PCL:SV total, and PICTS R
2. Age, ethnic status, marital status, PCL:SV total, and PICTS P

For aggressive incident reports:

3. Age, PCL:SV total, PICTS R
4. Age, PCL:SV total, PICTS P

For non-aggressive incident reports:

5. Age, ethnic status, marital status, PCL:SV total, and PICTS R
6. Age, ethnic status, marital status, PCL:SV total, and PICTS P

The first and second negative binomial regressions assessed the incremental validity among the variables associated with total incident reports. In the first equation, age was the only significant variable, suggesting that age provides incremental validity to all the other variables in this equation and that the other variables do not have incremental validity relative to age. In the second equation, the PCL:SV, the PICTS R and age indicated incremental validity relative to each other and to the other variables in the equation.

For aggressive incident reports, significant incremental validity was found for age and for the PICTS P in the third equation. This implies these two variables have incremental validity relative to each other and to the PCL:SV but that the PCL:SV does not provide incremental validity either to age or to the PICTS P. In the fourth equation, age and the PCL:SV indicated significant incremental validity relative to each other and to the PICTS R. The PICTS R does not have significant incremental validity to age and to the PCL:SV for this equation.

For non-aggressive incident reports, the fifth and sixth regressions demonstrated that only age was significant, suggesting that age adds incremental validity to all the other variables in the equation, but these other variables do not provide significant incremental validity to age.

In conclusion, age was significant in all cases of incident reports and the PCL:SV, the PICTS P and the PICTS R were significant in some cases. This does not fully support the main hypothesis that the PICTS R would produce incremental validity relative to the PCL:SV for predicting infractions over a 12-month period. The PCL:SV and the PICTS R did not produce incremental validity beyond age.

Implications

Implications of the Control Variables

Past research clearly indicated that age is the most robust predictor of adjustment and aggression in the prison setting (Camp, et al, 2003; Craddock, 1996; Toch et al., 1989). In an attempt to explain the age-prison adjustment relationship, some authors looked at the social and psychological changes that co-occur with aging (Wilson & Hernstein, 1986). These changes are thought to include developments in marriage, family, and employment that may lead to attachments to others and stronger community ties. Another perspective is that the process of aging includes psychological developments in which immediate hedonistic goals become replaced with more long term normative goals such as marriage (Adams, 1977). Marital status may be an age-related variable, because younger men are more likely to be unmarried. The demographic variable marital status in the present study was related to total incident reports which implied that inmates who were single received more overall incident reports.

Level of education was not significantly related to either the predictor or criterion variables. Inmates who had fewer than 12 years of education (along with other characteristics) portray a picture of offenders with marginal lifestyles in the community suggesting that they would be likely to have greater difficulty adjusting to prison. The findings in this study neither corroborated this picture nor replicated previous research (Faily & Roundtree, 1979; Finn, 1995; Flanagan, 1983; Toch & Adams, 2002; Wooldredge, 1991).

Higher disciplinary involvement for rule-breaking in general was previously found for the non-white, young, unmarried inmates in this study and other studies (e.g., Myers & Levy, 1978; Wright, 1991a). Significant findings in this study indicate that non-whites received more total and non-aggressive incident reports than white inmates, but not more aggressive incident reports. The results also indicated an equal percentages of white and nonwhite participants were involved in aggressive incident reports. About 7% (n=2) white inmates and 6% (n=7) non-white inmates were implicated in aggressive disciplinary reports at least once. This suggests that when looking at predicting aggressive incident reports, ethnic status is not a factor to include in the assessment. In an overview of inmates who commit aggressive infractions, the data suggest that 6% of all the inmates were responsible for the aggressive incidents over a 12 month period, supporting the idea of the "violent few" (DeLisi, 2003).

The other variable not significantly correlated with incident reports was confining offense. The prediction was that there might be continuity between offense and misconduct during imprisonment. Toch and Adams (2002) noted finding an effect; however, it was a weak effect between confining offense on adjustment. Although no significance was found in the present study between confining offense and infraction rates, it appears that it may be a strong enough variable to evidence a stronger relationship when there is more than a one year follow up or even a larger sample size. Furthermore, it has been suggested that the categorizations of aggressive versus non-aggressive confining offenses are too broad, missing more specific differentiations. For example, several authors discovered that inmates serving time for a variety of aggressive confining offenses (larceny, aggressive assault, and drug trafficking) received more infractions than inmates serving time for murder (Lee & Edens, 2005; Toch & Adams, 2002). This may provide an area for future research.

Implications of Incident Reports (Criterion Variable)

Base rates for criminal behavior, in general, fall in the 20 to 80 percent range (Andrews & Bonta, 2003). In this study the base rate for the occurrence of any infraction was 34.9% which allows room for risk assessments to make significant contributions. The base rate for non-aggressive infractions was 31.5%; and the base rates for aggressive infractions was 6.2%. The majority of inmates with more than a single infraction tended to have the same types of infractions; there were several inmates who received both aggressive and non-aggressive incident reports. This explains why the base rates for aggressive and non-aggressive incident reports do not add up to the total base rate: some inmates had both types.

Predicting aggressive incident reports would be more difficult due to the low base rates. When an event occurs infrequently and has a low base rate, prediction is easy in one sense: the best strategy is to predict that this event will *not* occur. Yet there are events of such critical importance (e.g., aggressive behavior in prison) in which the ability to forecast them offers enormous benefits.

In this study, 35% (n=51) of the participants were responsible for the 109 incident reports. Of those who committed infractions, half received a single infraction; the other half received two or more incident reports. Most of those receiving more than one incident report received them exclusively either for aggressive or non-aggressive misconduct, not both types. There was an exception involving four inmates, who received both types of incident reports. Of these four inmates, two received two incident reports, one aggressive and one non-aggressive incident reports. The third inmate received two non-aggressive and one aggressive incident report. The fourth inmate received an extraordinary number of incident reports compared with the other three. This individual received 11 non-aggressive incident reports and 9 aggressive incident reports.

Upon closer inspection of the paper file of the inmate who received 20 incident reports, notations indicate that in the past he was diagnosed with schizophrenia of the paranoid type. This may suggest that this inmate still suffers from the illness and as a result experienced great difficulty adjusting to prison, or perhaps it was his chronic and severe acting out behaviors that led to the chronic and severe diagnosis of schizophrenia. The records provide no further information on this individual. The idea of the mentally ill in prison touches a sensitive and worrisome area of concern.

Concerns exist about the number of persons with mental illness in jails and prisons. A higher proportion of individuals with mental illness are arrested than are those without mental illness; the proportion of those with mental illness in prison is higher than in the general public (Lamb & Weinberger, 1998). The Bureau of Justice Statistics reports that from 1995 to 1997, 7% of federal inmates were considered mentally ill compared with 16% of state prison inmates, and 16% of those in local jails (Ditton, 1999). One study found that federal inmates with mental illness were twice as liable to be involved in fights than other inmates (21% and 9% respectively), nearly three times as liable to be incarcerated for a violent offense, and more liable to be charged with a rule violation while incarcerated than inmates not identified as mentally ill (Ditton, 1999). The vast majority of individuals with serious mental illness do not pose a greater risk of danger than the general population. However, there is a subgroup that tends to be more dangerous, and unfortunately, which increases the stereotype for all persons with mental illness (Lamb & Weinberger, 1998).

Implications of the Psychometrics Variables

Studies on the PCL:SV have consistently shown that the total and Part II scores are better than Part I at predicting institutional adjustment (Belfrage, Fransson, & Strand, 2000; Doyle, et al., 2002; Harpur, et al., 1989; Salekin, et al., 1996; Walters, 2003; Young, Justice, Erdberg, 2004). The findings of the present study indicate that Part I of the PCL:SV was not correlated with incident reports, but that the total and Part II scores were significantly correlated with incident reports. This implies that the behavioral correlates of psychopathy (i.e., chronically unstable antisocial lifestyle, criminal versatility, juvenile, delinquency) were better than the traditional psychopathic personality traits (callousness, egocentricity, glibness) in predicting infractions. It may also imply that using a file-only review for rating psychopathy does not provide enough information for rating the Part I items, as compared with more abundant factual information about documented behavior found in files for rating Part II.

Both the PICTS P and R composite scales have demonstrated predictive ability with adjustment (Walters, 2005b, in press a, in press c). In the present study, both the PICTS P and R composite scales were significantly correlated with incident reports replicating previous studies. Of note, this is the first investigation in which the PICTS P significantly correlated with aggressive incident reports. This implies that aggressive incident reports were planned. That is, aggressive acts may have been enacted against other inmates or self in order to obtain a desired outcome—suggstive of proactive criminal thinking. The aggressive activity was not hot-headed impulsive reaction to a situation but rather one that was planned and calculated.

Similarly, the PICTS P was the only psychometric variable to have significance for AUC in this study. This runs counter to what was expected and to what has been previously found (Walters, 2005a, 2005b, in press d; Walters & Geyer, 2005). It was expected that the PICTS R would be associated with aggressive infractions because reactive aggression has been shown to be the more pervasive form of violent crime (Cornell, et al., 1996). Reactive aggression occurs in response to environmental stress and is correlated with hostile attributional biases not with outcome expectancy (i.e., goals) (Walters, et al., 2005). Instead the PICTS P scale, a measure of proactive ideation that is instrumental and with an end goal in mind, was predictive of aggressive incident reports. This implies that aggressive behavior was tied to having expectations of a positive outcome. That is, inmates committed aggressive acts with a purpose in mind and, if achieved, would bring a sense of pleasure. What the data do not differentiate is the extent to which aggressive acts were self- or other directed. It would be a view into possible psychopathic tendencies.

Studies illustrate that individuals with psychopathy are characterized as having shallow emotions; they seldom commit violent crimes while intensely emotionally aroused (Williamson, Hare, & Wong, 1987). This is in contrast to non-psychopathic individuals who were found to assault during extreme emotional arousal (Cornell, et al., 1996). This suggests that individuals with psychopathy commit more instrumental violence while staying cool and maintaining an expectation that something they desire will result from their aggressive actions (Cornell, et al, 1996). Cornell, et al., (1996) also contended that instrumental offenders can be identified by the presence of instrumental acts of aggressive behavior but not necessarily the absence of reactive aggression.

In a supplemental analysis of the present investigation, Part II had incremental validity relative to Part I for total, aggressive, and non-aggressive incident reports. However, when they were combined with other variables, Part II no longer had incremental validity relative to Part I. Part I was not significantly linked to incident reports; therefore, it is easy to understand that Part II increased its predictive ability. When demographics were added, however, incremental validity was no longer indicated for Part II. Apparently the other variables had a strong enough correlation with incident reports so that Part II could no longer make a significant contribution to these variables. These findings suggests the need for continued research in this area.

Measures commonly used for evaluating predictive accuracy include the percent correctly classified, sensitivity and specificity, and positive and negative predictive power (Baldessarini, Finkelstein, & Arana, 1983). The problem in using these measures is that the tool's apparent usefulness is highly dependent on the base rate (or prevalence) of aggressive incident reports, the selection ratio (i.e., proportion of inmates predicted to be violent), or both.

Both the PCL:SV and PICTS scales evidenced adequate specificity, but it was at the expense of sensitivity for each of the psychometrics. That is, the cutting scores appeared to be more efficient in identifying accurately those individuals who would not commit certain types of incident reports; however, their ability to identify those who would commit such institutional offenses was considerably weaker. This indicates that the psychometrics were better at assessing the true negative rate than they were at assessing the true positive rate; they were better at specifying those who scored below the cutting score and who did not receive incident reports than they were in reacting sensitively to those who scored above the cutting scores and who did receive incident reports. In predicting aggressive behavior before it actually occurs, particularly when the base rate of occurrence is low, requires an instrument with very strong sensitivity and specificity.

Additionally, there was stronger negative predictive power (the probability that incident reports were not present when the test scores were below the cutting score) than positive predictive power (the probability that incident reports were present when the test scores were above the cutting score) in this sample of inmates. One of the strongest findings of predictive power in this study was a 41% probability that incident reports (total) will be present when the test scores for the PICTS R are above 60. Other strong findings indicated probabilities in the 90% range for the occurrence of no aggressive incident reports when the PICTS P cutting score is below 55, when the PICTS R is below either a 55 and 60 incident reports, and when the PCL:SV Total is below 18.

These traditional indices of accuracy, such as the negative predictive power and the positive predictive power obviously depend on the selected cutting score. Nonetheless, classifications such as sensitivity, specificity, negative predictive power, and positive predictive power offer means for assessing the construct of accuracy.

Implications of Incremental Validity

The primary concern in correctional institutions is maintaining safety (Cullen, et al., 1993). Infractions of greatest concern are those involving aggression. This study was an attempt to establish incremental validity for more accurately predicting inmates who would receive the greatest number of incident reports during a 12 month period of incarceration in the institution where the study took place. The results of the incremental validity analysis were not fully consistent with what was hypothesized. It was expected that the PICTS R relative to the PCL:SV total score would have better accuracy in predicting incident reports. Instead, the PICTS, the PCL:SV total, and age were shown to have incremental validity relative to each other for total incident reports. Incremental validity for these variables was not found either for aggressive incident reports or for non-aggressive incident reports. Thus, the inconsistent findings of joining the PICTS R with the PCL:SV total for incremental validity suggest the need for a larger sample or for an increase in follow-up time in order to increase the overall effects.

In this study, age added incremental validity relative to the other demographics and to some of the psychometrics. According to previous research, age has been shown to be the most robust predictor of adjustment. As age increased the frequency and severity of the disciplinary infractions decreased (Camp et al., 2003;Craddock, 1996;

Faily & Roundtree, 1979; Flanagan, 1983; Goetting & Howsen, 1986).

In conclusion, the PCL:SV performed better when it was paired with the PICTS R scale than when it was paired with the PICTS P scale. This implies that the PICTS R and the PCL:SV make a better pair for future prediction than the PICTS P and the PCL:SV.

In a time when financial considerations are integral to institutions, the findings of this study indicate that it would prove most resource efficient to assess inmates under a particular age in lieu of testing inmates of all ages. The significance of the incremental validity of the PCL: SV, of the PICTS R, and of age relative to each other suggests that using easily obtainable information such as age can be an initial variable useful for narrowing the focus for inmates needing further risk assessment, thus reducing overall costs.

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Implications of Using Two Statistical Models

The present study may seem like a dual study with the first study investigating incremental validity and the second one comparing two different statistical models. This second inquiry was not intended at the outset. When the data were collected and the distributions analyzed, the skewness (non-normalcy) of the distributions drew concern. Along with using the traditional methods, a more fitting statistical model to address this concern became an unplanned undertaking. The negative binomial regression model was the result of this search. Thus the 36 analyses were conducted using both the traditional methods and the less well known model. Comparing the traditional linear correlations and the logistic regression analyses with the negative binomial regression model produced intriguing and noteworthy results. Overall the traditional statistical models produced significant findings for 4 (11%) of the correlations/regressions and the negative binomial regression found significant findings for 23 (64%) of the univariate/multivariate regression analyses. The negative binomial regression found the same significances as the logistic regression in addition to others. This implies that the negative binomial regression is a more sensitive statistic for count data. In conclusion, this model opens the doors for its use in future research with count data in the social sciences, and for re-analysis of previous research originally analyzed by other less sensitive models with count data.

Contributions to the Field

Deriving methods for accurately predicting which inmates will receive more aggressive and assaultive infractions continues to be a pressing concern for correctional facilities. Predicting behavior is a challenge; predicting behavior that occurs infrequently such as aggressive infractions is an even greater challenge. Although traditional risk assessments that rely on history, behavior, and interpersonal factors have done moderately well in risk predictions, improvements in terms of additional variables or incremental validity continue to be sought to improve accuracy. This study was an attempt to advance the prediction of an infrequently occurring, critically important event. In addition, this study not only provided continued advancement of the role of cognitions in behavior choices, but considered the role of cognitions in a less often studied but very important environment and population.

Walters (2001b) made a plea to the field of criminology to consider the impact that cognitive factors have as variables related to prison adjustment because it has largely been ignored. According to Walters, crime is seen as a function of a person's belief system: "How people view themselves, the world, and the relationship of the two can go a long way in explaining why certain individuals are willing to risk their lives and freedom for a few dollars or a fleeting sense of power or control" (p. 131). To a large degree this statement is reminiscent of Beck's cognitive triad for clinically depressed. Individuals, who are characterized by having negative beliefs about themselves, about the world, and about their futures (Beck, 1963, 1964). Studies have been looking to cognitions as a variable for making further strides in predicting psychopathology and criminology, finding that cognitions add an important contribution. For example, Seager (2005) suggested that almost half the variance in violent criminal history was accounted for by measures of impulsivity and self schema for a hostile world.

The present study aimed to bring the relevancy and significance of cognitive factors to the forefront, hoping to stimulate further research between cognitions and criminology. Cognitive theories and studies supporting the importance of cognitive factors integral to maladaption and criminal behavior have paved the way to program development which was based on similar theory and research. The Bureau of Justice

Statistics (2003c) indicate that 100% of federal correctional facilities offer psychological and psychiatric counseling (including programs) compared with 66% of state and 46% of private facilities. Programs such as the Lifestyle Change Program (Walters, 1990, 1996) which emphasize cognitive skills training have shown to be effective for high risk individuals (Walters, 1999). Additionally, other studies have demonstrated the effectiveness of cognitive behavioral programs for improving cognitive restructuring and increasing cognitive skills in reducing criminal behavior among offenders (Wilson, Bouffard, & Mackenzie, 2005).

Limitations of This Study

Some possible limitations of the present study should be addressed. These encompass issues regarding information gathering, replication, generalizability, and predictive accuracy.

Information Gathering

The PCL:SV permits one item to be omitted from each Part I and Part II subscales and subsequent prorating of the scores. For the majority of the participants, file information was insufficient for rating Part I personality characteristics such as superficialness and grandiosity. In general, files varied in the amount of information they provided; some inmates' files were comprehensive sources of information and others provided minimal information. Minimal information was found especially for those of inmates who were non-citizens. It has been suggested that non-citizens' files often underestimate information or lack relevant information (Camp, et al., 2003). Considering the statistic that nearly 25% of federal prisoners are non-citizens (BJS 2003c), the lack of accuracy in records may have impacted the scores of the PCL:SV.

Generalizability

Individuals selected for the study were those who entered the corrections facility at a selected time; they were not a randomly selected group of offenders. These inmates entering at that time may have had something similar or may have come to this correctional institution because of changes in the judicial or political milieu. It can be argued that this may not be a representative sample of all offenders.

The fact that the participants were adult male offenders who committed federal offenses resulting in incarceration in a medium security federal facility suggests some homogeneity among the group participants. Although there are a number of advantages to having a highly homogenous participant sample (Kendall & Lipman, 1991), there is also the disadvantage of generalizing the results to other types of prisons (e.g. state), levels of security (e.g., maximum), age (e.g., adolescents), and gender (female inmates). Therefore it is important to consider not only the sample from which studies were conducted, but also onto how to generalize these findings.

Finally, there are concerns about generalizing risk assessment variables to other cultures. Returning to the statistic that nearly 25% of Federal prisoners are non-citizens (BJS, 2003c), there might be concerns about literacy (can these inmates read and speak the English language), about cultural differences, and about interpretations of English words and expressions.

Improving Predictive Accuracy

There are a number of areas in which predictive accuracy may have been compromised. These include the reliability of the measures, the heterogeneity of offenders' prison experience, interrater reliability, and the length of the follow up period.

One of the ways to improve predictive accuracy is through the use of reliable measures. The criterion measure used in this study, derived from official records of institutional disciplinary infractions, has been criticized as being a fairly poor index of the true level of violence and of other forms of antisocial conduct in prison settings (Light, 1990; Poole & Regoli, 1980). Although these data provide easily accessible, inexpensive means to a wealth of information, the related short comings should be kept in mind as a possible source of error.

Some offenders may have arrived at this facility with no prior history of incarceration. Other inmates may have been transferred from another facility or were returning to serve another term. This may be a source of variability which confounded the data in this study.

The interrater reliability established for the PCL:SV was in an acceptable range but it was not as high as other studies have reported. This may have occurred because one of the raters is a staff member who had access to additional information from contact, from observation, or from overhead details about some of the inmates. This additional knowledge could have influenced the ratings on the PCL:SV, especially for the difficult-to-rate items. This rater may have had adequate information to rate the items that were otherwise omitted by the main rater who was not a staff member.

Like disciplinary reports, low base rates with a follow up of only one year are difficult to predict precisely because it is easer to predict that one will *not* get an aggressive disciplinary report (which in this sample would be correct 87.7% of the time) than trying to use a psychometric measure with lower overall accuracy. Hence, the results have limited practical utility. Longer follow up base rates would be larger; this would improve prediction accuracy by obtaining a larger overall sample of the event.

Directions for Future Research

Areas for future investigation are spawned by this study. Future studies might explore the newness of the prison experience for inmates in a single sample, longer follow ups, and using the PCL:SV and the PICTS R as an initial screen.

First timers lacking prison experience may have had a more difficult time adjusting to prison life when compared with the seasoned inmates. The seasoned inmates and transfers may not have experienced the “transition shock” described by Toch and Adams (2002). This may then have an impact on the accuracy of prediction during their first year at the prison where this study took place, suggesting that a longer follow up period is required. Future studies might consider a 2 year follow up—which would also benefit the base rates.

It might be useful to use the findings from this study as an initial screen for inmates who pose a risk for adjusting to prison. A follow up measure could then be used to identify inmates who pose more of a risk for aggressive incident reports. This, too, is an area for future research. The present study set out to explore the combined elements of two risk assessment measures for incremental validity in predicting inmate adjustment. Although the findings were not fully consistent with the hypotheses, this study highlights the concept of cognitive factors in risk assessments, of their importance, and of the need for their continuing development.

This present investigation may have been a study seeking answers to the question about whether or not a measure of psychopathic personality, of affect, and of behaviors might have better predictive value if cognitions (i.e., ideation) were added into the equation. In essence, it sought to understand if thoughts, in addition to personality and behavior, might predict future behavior better than either one alone. It also asked whether or not the blended approach of the PCL:SV for assessing risk could be enhanced by an actuarial self-report such as the PICTS. Although the results may be limited in scope, they were nonetheless profitable for the research community because they point the direction to future research.

Summary

The importance of accurately assigning risk in correctional institutions cannot be overlooked. This study sought to contribute to the body of research with a means for predicting misconduct more accurately among inmates at a federal facility over a 12 month period. The psychometrics involved in this study have shown significance with incident reports and so were used in combination for investigating incremental validity. The PICTS R composite scale and the PCL:SV total score indicated significant incremental validity, but not beyond age. The equation that was significant included the PCL:SV total, the PICTS R, and age (when the other demographics, ethnic status and marital status were blocked) in relation to total incident reports. Incremental validity was not found among the other categories of incident reports (aggressive and non-aggressive); this suggests that this equation may provide a starting point for assessing risk among offenders. Further empirical examination of this equation is an area for future research. A number of possible limitations of this study were considered, including factors affecting information gathering, generalizability, and predictive abilities. The inclusion of cognitive variables into the area of criminology can serve only to expand the ability of researches to forecast adjustment to prison.

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