25-YEAR OUTCOMES OF AN IN-PRISON THERAPEUTIC COMMUNITY IN TEXAS

by

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The identification of a person's risk of recidivism and treatment needs is the necessary first step for justice agencies in providing them the appropriate care and services designed to reduce their likelihood of future involvement with the justice system. The current study begins with an overview of challenges within the justice system and with longitudinal examinations of recidivism. Next, a brief history of treatment in the justice system in provided, followed by an explanation of the Risk-Need-Responsivity (RNR) model. The current study then draws on the framework underlying the RNR model to investigate the impact of in-prison therapeutic community treatment and community-based aftercare on rearrest and reincarceration over a period of 25 years.

Introduction

The United States is concurrently facing challenges with mass incarceration and the substance use epidemic. These two simultaneous challenges are interrelated. As of May 21, 2022, the Federal Bureau of Prisons reports that 45% of individuals currently incarcerated in federal prisons are serving time for drug-related offenses, which represents a far larger proportion compared to any other offense category. Furthermore, a recent meta-analysis reported that the pooled prevalence estimate for substance use disorders within the criminal justice (CJ) system was 51% among females and 30% among males (Fazel et al., 2017). In comparison, 7.4% of the general population aged 12 or older met the criteria for a substance use disorder in 2018 (Substance Abuse & Mental Health Services Administration, 2019). Left untreated, people with a substance use disorder who are released from jail or prison are at heightened risk of recidivating and experiencing other adverse health outcomes; for example, justice-involved people are 12.7 times more likely to die from an overdose in the first 2 weeks after release (Binswanger et al., 2016). Moreover, justice involvement greatly limits future opportunities for employment and housing, and also negatively affects an individual's relationships with their friends and family (Couloute, 2018; Kopf, 2020; Pager, 2003). These negative consequences increase the risk that a person will return to substance use and/or criminal behavior. For this reason, it is essential for CJ agencies to identify criminogenic needs (e.g., substance use) so that appropriate interventions can be delivered to reduce the negative personal and societal impacts of crime. It is therefore timely to examine whether current practices in the CJ system can identify who is going to reoffend over an extended period of time after release, and perhaps more importantly, identify individuals who are most likely to benefit from intensive in-prison treatment.

Defining Recidivism

Texas ranks tenth in terms of incarceration rates compared to the rest of the United States, with an incarceration rate of 840 per 100,000 people in prisons, jails, and other systems of confinement (Widra & Herring, 2021). Approximately 251,000 people are incarcerated within Texas – 163,000 in state prisons; 55,000 in local jails; 27,000 in federal prisons; 4,300 youth in juvenile detention facilities; and 1,400 under involuntary commitment (Widra & Herring, 2021). Further, due to the rate at which people cycle through local jails, 505,000 different people are booked into local jails in Texas every year (Widra & Herring, 2021). The number of people in Texas's CJ system jumps to 726,000 when those under community supervision are included (368,000 on probation and 107,000 on parole; Widra & Herring, 2021). And based on recent Texas Criminal Justice Coalition testimony from policy analyst Douglas Smith to the Texas House Committee on Corrections in 2016, the return to custody rate (a measure of recidivism) for those released from a Texas prison has dropped to 21.4%, yet the more than 46% of those leaving prison in 2011 were rearrested within 3 years of release (another measure of recidivism; House Committee on Corrections Texas House of Representatives Interim Report, 2016).

Recidivism rates are difficult to compare across states due to the differences in how each state defines and measures criminal recidivism. While there is no “right” way to measure recidivism, significant challenges arise when drawing comparisons across studies with different recidivism definitions and measurement contexts (e.g., data source, data collection methodology). Historically, recidivism is most often defined as reincarceration within 1 to 3 years of release from prison (Andersen & Skardhamar, 2017). As Ruggero et al. (2015) explain, recidivism is typically calculated as a percentage of people in a specified group (e.g., individuals released from any Texas prison in 2021) who meet some criteria (e.g., rearrest, a new conviction, or new incarceration) in a specified amount of time (e.g., 3 years post-release). Recidivism is frequently operationalized as a dichotomous variable (Yes vs. No) to indicate whether there has been a new arrest, conviction, or imprisonment (e.g., Farrington, 2020; Fox et al., 2021; Yukhnenko et al., 2020). Rearrest rates vary widely, but typically fall between 40% to 70% (e.g., Hanson & Morton-Bourgon, 2009; Ostermann, 2011; Ostermann & Caplan, 2013; Stelle et al., 1994). Defining recidivism as rearrest generally leads to higher recidivism rates compared to using convictions or imprisonments. Using arrest patterns as a proxy for recidivism is biased because arrests are heavily influenced by police arrest policies; as such, arrest rates tend to be higher for young men living in impoverished areas compared to, for example, domestic violence crimes that often occur in private and thus are less likely to be detected by law enforcement (Marmolejo, 2016). Conversely, using reconvictions or reincarcerations as definitions for recidivism can under-count actual reoffending since they rely on both the detection of a crime and evidence to convict a person. Reconviction rates typically range between 40% to 60% (e.g., Armstrong & McNeill, 2012; Wartna et al., 2010, as cited in Andersen & Skardhamar, 2017), and reincarceration rates generally yield the lowest recidivism counts, usually within the range of 30% to 50% (e.g., Armstrong & McNeill, 2012; Nadesu, 2008; O'Donnell et al., 2008; cf. Skardhamar & Telle, 2012). Given these variations, how recidivism is defined is dependent upon how the group, criteria, and timeframe are defined. Regardless of how an agency, state, or program chooses to define recidivism, a certain degree of error is always expected. Any measure of recidivism is understood to underestimate "true" recidivism rates because they are contingent on official criminal records data, which are fallible and only document crimes that resulted in either arrest or conviction (National Institute of Justice [NIJ], 2008).

Rather than operationalizing recidivism as a dichotomous outcome within a specified period of time, some studies instead analyze "time at risk," or the total amount of time since a person was released from prison to the date they are rearrested, reconvicted, or reincarcerated. Within that, there is the added complexity of whether only time spent outside of prison should be included or not. For example, some contend that time in prison should be excluded from the follow-up period (Farrington & Davies, 2007), while others argue for its inclusion because some crimes may be committed while an individual is incarcerated, such as drug- and violence-related crimes (e.g., Gillespie, 2005; Wolff et al., 2007). Moreover, the at-risk environment is another key consideration when comparing results across studies. A person's risk level post-release may depend on the level of community supervision and release requirements (e.g., whether drug testing is a requirement). While stricter release requirements may reduce the likelihood of someone committing a new criminal offense, it could also increase the likelihood of probation/parole revocation due to the stricter requirements (NIJ, 2008). Indeed, recidivism rates are higher when technical violations are included as cases of recidivism compared to when rates only reflect cases of new criminal offenses.

Longitudinal Examinations of Recidivism

A common practice in empirical research has been to identify rates of recidivism within a specified period of time following release. According to Andersen and Skardhamar (2017), it is common for studies to measure recidivism over 2 years post-release (e.g., Armstrong & McNeill, 2012; Farrington & Davies, 2007; Graunbøl et al., 2010). Naturally, as the follow-up period is extended, recidivism rates increase. In a Dutch sample of recently released individuals, the recidivism rate increased from 43% after 1 year to 56% after 2 years, 62% after 3 years, and 74% after 8 years (Wartna et al., 2010, as cited in Andersen & Skardhamar, 2017). Notably, individuals are most at-risk of reoffending shortly after they are released, and their risk for reoffending gradually declines year after year (e.g., Armstrong & McNeill, 2012; Beck & Shipley, 1989; Bowles & Florackis, 2007; Skardhamar & Telle, 2012). A recent report released by the Bureau of Justice Statistics (BJS) followed all individuals released from state prisons across 30 states in 2005 for 9 years (see Alper et al., 2018). During that period, 83% were arrested at least once during the 9 years after they were released. This study is unique in the length of its 25-year follow-up period, as many studies only track recidivism up to 3 years post-release. In the 2018 BJS report, the recidivism rate more than doubled at nine years compared to three – that is, 60% of arrests occurred after the third year.

While examining the prevalence of recidivism rates provides an estimate for the number of people that reoffend, these studies do not provide information on ways to improve desistance. For example, rehabilitation (e.g., therapeutic communities, education/awareness programs) and punishment (e.g., punitive sanctions) strategies have demonstrated varying degrees of success at reducing recidivism rates. One early study assessing recidivism rates over 3 years post-release compared the two strategies and found that rehabilitation was more effective than less formal punishment at reducing the likelihood of recidivism among people with arrests for driving while intoxicated (DWI); however, among individuals for whom it was their first arrest for DWI, less formal punishment was most effective in deterring drunk driving (Taxman & Piquero, 1998). Similarly, Yu (2000) found that sanctions were not effective among individuals with severe alcohol problems; rather, these individuals required treatment services to reduce drunk driving recidivism. A recent examination by Morash et al. (2017) underscored the importance of risk level in the effectiveness of treatment versus punishments among a sample of women with felony convictions. For women classified as high risk, treatment was associated with reductions in recidivism and punitive responses were related to increases in recidivism. In contrast, among low-risk women, treatment was related to higher recidivism and punitive responses to decreased recidivism.

Additional studies are needed to understand patterns of reoffending and reincarceration over long periods of time to identify factors predictive of recidivism. Since desistance is a process that fluctuates over time, the longer the follow-up period, the better. This information can then be used to inform practices and therapeutic interventions intended to reduce rates of recidivism. For example, a static factor consistently implicated with reoffending is age. As reported by Durose and Antenangeli (2021), among individuals released in 2012 across 34 states, 81% of those aged 24 or younger were arrested within 5 years; in comparison, 74% of individuals aged 25-39 and 60% aged 40 and older were arrested in the same period. Additional studies seeking to uncover other predictors of recidivism can assist CJ agencies in more accurately determining a person's risk level and identifying individual needs for services. For instance, finding that amendable factors, such as unemployment, are associated with recidivism could provide justification for the implementation of post-release programs that address employment.

Longitudinal examinations of recidivism provide an opportunity for researchers to use statistical approaches that maximize the variance accounted for (e.g., survival regression, latent growth modeling). Historically, there has been a lack of emphasis on people who chronically engage in crime and on the impact of conditions of confinement (Kazemian, 2007). Early analytic strategies for studying change over time were limited to two timepoints and were incapable of simultaneously examining both group-level and individual-level growth (Preacher et al., 2008). By comparison, longitudinal designs can perceive the shape and direction of change over time (i.e., trajectories) as well as the sources (e.g., variables associated with change over time) and consequences (e.g., whether change over time in one variable is related to change over time in another variable) of change (Preacher et al., 2008). Compared to data with only two timepoints, longitudinal data may test hypotheses about differences between individuals in growth trajectories (i.e., interindividual differences) and background characteristics related to growth patterns (i.e., intraindividual differences; Willett, 1989; Willett & Sayer, 1994). The present study uses survival regression and latent growth modeling to examine amendable factors that CJ agencies can target using evidence-based interventions to meet the needs of people who are incarcerated that directly relate to criminal recidivism. Analyses also examine group-level differences associated with chronic patterns of reoffending.

Across studies, one effective method to reduce subsequent recidivism among people in the CJ system is to provide services and treatment to meet the needs of people both while they are incarcerated and upon their release into the community (e.g., Galassi et al., 2015; Wexler &

Prendergast, 2010; Wilson et al., 2011). It is common for people to experience setbacks in their road to desistance; however, discontinuing the cycle in and out of the justice system requires effective interventions that target factors associated with a heightened risk of future offending and that reinforce a person's ability to successfully reintegrate into society (Kazemian, 2021).

History of Treatment in the Criminal Justice System

The first paper published consolidating findings on the effectiveness of treatment delivered in custodial settings was by Kirby (1954). He reviewed four studies comparing recidivism rates between individuals who received correctional counseling and those who had no treatment. Three of the studies reported that correctional counseling significantly lowered recidivism rates (see Fox, 1950; Healy & Alper, 1941; Hoffman, 1943) and one reported no treatment effect (see Bowler & Bloodgood, 1935). Successive reviews expanding the number of studies published on the effectiveness of correctional treatment reported successful outcomes following 50-60% of treatment programs (Bailey, 1966; Logan, 1972).

The prevailing belief that some prison-based rehabilitation programs can effectively reduce recidivism rates was undercut in the 1970s by a review published by Martinson and associates (Lipton et al., 1975; Martinson, 1974) concluding that "nothing works" (despite replicating previous findings that 50-60% of studies in this domain supported the effectiveness of rehabilitation programs). Consequently, the philosophy of rehabilitation was replaced with one of retribution amid rising prison populations and public outcry over soaring crime rates. As detailed by Fallin et al. (1992), legislators responded by enacting determinate sentencing and persistent felony offender laws. Widespread substance use in the 1980s led to stricter sentences for people convicted of using or distributing drugs, which resulted in ever-expanding prison populations consisting largely of individuals with substance use disorders. The prevalence of substance use and substance use disorders among justice-involved populations eventually led CJ agencies to begin implementing prison-based substance use treatment programs as a way of curbing recidivism and overcrowding. The overarching belief of retribution over rehabilitation began to subside following evidence that certain types of prison-based substance use treatment programs (e.g., therapeutic communities) were effective at reducing recidivism.

Today, CJ facilities that incorporate treatment for substance use disorders into programming have shown it to be an effective way to improve outcomes among this at-risk population (Knight et al., 1999; Wexler & Prendergast, 2010). A common approach among prisons has been to integrate therapeutic communities to meet the unique needs of people involved in the CJ system. There are many studies that report therapeutic communities lead to positive changes in substance use, criminal behavior, and mental health even among people with the most severe problems (De Leon, 2010; Vanderplasschen et al., 2013).

Therapeutic communities offer several advantages over other types of treatment programming in correctional contexts. These programs rely on staff members to act as role models and peers to reinforce positive changes in attitudes and behavior (National Institute on Drug Abuse [NIDA], 2020). In an effort to engage people as co-producers of their own desistance (and their peers'), programs often employ former service users because of their ability to relate with clients on a more personal level. Therapeutic communities strive to foster an atmosphere of mutual help, where participants are encouraged to be open and honest, develop self-reliance, learn ways to manage negative emotions, and accept responsibility for their actions (Wexler & Prendergast, 2010). This unique environment is believed to increase the effectiveness of whatever treatment program is being delivered (Brookes, 2010). One distinctive feature of therapeutic communities that differs from other treatment modalities is the comprehensive range of interventions provided. It is common for therapeutic communities to incorporate elements of cognitive-behavioral therapy to assist clients in developing insight into how their (mis)interpretation of events may engender emotions and thoughts that justify criminal behavior (NIDA, 2020). The emphasis on social functioning and peer influence comes from Bandura's (1971) Social Learning Theory, which holds that people learn through observing, imitating, and modeling each other's behaviors. Based on this, a central tenet of therapeutic communities is positive peer pressure and confrontation aimed at promoting prosocial behavior among clients (De Leon, 2000, 2015; Vanderplasschen et al., 2014).

Others have questioned the utility of therapeutic communities in custodial settings because their focus on peer influence has the potential to affect clients in negative ways (Roybal, 2011). Specifically, Sutherland's (2015) Differential Association Theory has been used to explain how people learn the values, techniques, and motivations for criminal behavior through interacting with others. For example, some have argued that placing low-risk individuals in high-intensity treatment programs (such as therapeutic communities) can heighten their risk of future offending (Bonta et al., 2000). The potential of low-risk clients to learn and imitate the antisocial behaviors of their high-risk peers highlights the importance of understanding the aspects of treatment responsible for positive change, and for whom they work. One such important aspect of treatment is the tailoring of treatment programs to meet the unique needs of individuals (Bonta & Andrews, 2007). The group-based model of therapeutic communities assumes a "one size fits all" protocol for rehabilitation, and therefore makes this approach limited in how it can be tailored for individuals. Moreover, the change in environment after release from in-prison therapeutic communities may hinder clients' adoption of newly learned prosocial behaviors, which may also explain why some people return to criminal behaviors after they are released.

Considering the advantages and limitations of therapeutic communities, there has been a push for community-based therapeutic communities to provide aftercare once these individuals are released from prison (Wexler & Prendergast, 2010). A review by Galassi et al. (2015) found that therapeutic communities with aftercare were more effective at lowering recidivism and substance use relapse rates than programs without aftercare. This was attributed to the aftercare component supporting clients as they transition from prison back into the community by teaching life skills and coping strategies relevant to life post-incarceration (Hiller et al., 1999; Prendergast et al., 2004). Most important, aftercare is effective at reducing substance use-related criminal behavior (Galassi et al., 2015). In the review by Galassi and associates, all but one aftercare program reported successful outcomes – the unsuccessful program was the only one that involved *mandatory* aftercare (see Welsh et al., 2014), suggesting motivation plays a role in the success of aftercare programs. Knight et al. (1999) reported that high-risk clients who were released from an in-prison therapeutic community were significantly less likely to recidivate compared to those who received treatment but did not complete aftercare, and those who received neither treatment nor aftercare. Overall, it is important for CJ personnel to support people in the wider social and community contexts that they live after they are released (e.g., religious organization, employment, housing, treatment).

In summary, experts in the fields of psychology and CJ acknowledge the importance of providing evidence-based treatments in carceral settings (e.g., Sacks et al., 2008; Warner & Leukefeld, 2001; Wilson et al., 2011). This understanding comes not only from a public health and economic perspective, but also the inherent human nature to help rehabilitate others where possible. It is therefore a necessity to discern what makes treatment programs effective so that standard practices can be structured around the ultimate goal of preventing recidivism. One aim of the current study is to identify whether some people respond better than others to intensive custodial treatment (i.e., an in-prison therapeutic community), and personal characteristics associated with reductions in future reoffending.

Risk-Need-Responsivity Model

The RNR model (Andrews et al., 1990) is widely used in CJ settings as a model of rehabilitation (Bonta & Andrews, 2016; Cullen & Jonson, 2016). First developed in the 1990s, the RNR model represents a paradigm shift in the field of CJ wherein there has been a push towards providing individualized services that directly target clients' risks and criminogenic needs that increase the likelihood recidivism. According to the RNR model, there are three core principles that CJ agencies can reference in developing risk assessments and effective rehabilitation programs that produce significant reductions in recidivism (Bonta & Andrews, 2007). As described in Bonta and Andrews (2007), the Risk principle states that a person's likelihood of recidivating should be determined such that more intensive treatment options can be reserved for those individuals at the greatest risk of reoffending. In other words, it is important to ensure that a person's risk level in terms of recidivism is aligned with the level or intensity of services provided to them. Next, the Need principle asserts that individuals must have their criminogenic needs identified using valid and reliable assessments, and subsequently receive treatment that targets those needs. Finally, the Responsivity principle describes how the treatment should be delivered in order to receive maximum benefit from a given program by adapting to the individual's strengths, motivations, and learning style.

The Risk principle asserts that the most effective rehabilitation programs are proportional to an individual's risk of reoffending. The key point is that intensive services should be reserved for people at highest risk for recidivating to maximize treatment effectiveness. Similarly, those at a lower risk of recidivating appear to respond as well (or in some cases, better) to less intensive programming. For example, Bonta et al. (2000) reported a 15% recidivism rate when clients categorized as low risk for reoffending received minimal treatment; in contrast, low-risk clients who received intensive treatment had more than double the recidivism rate (32%). Among those at high risk for recidivating, delivering intensive treatment resulted in a much lower recidivism rate compared to not receiving any treatment (32% vs. 51%, respectively). As such, CJ agencies rely heavily on assessment tools in determining an individual's likelihood of recidivating to provide the appropriate treatment intensity and modality (Campbell et al., 2007).

There are numerous factors that are predictive of future recidivism – often divided into static and dynamic factors (Bonta & Andrews, 2007). Static risk factors are immutable and cannot be directly targeted for change (e.g., criminal history). It is not possible for static risk factors to be reduced or to account for behavioral changes that may lessen an individual's risk of recidivism. Static factors contribute to a person's risk of future criminality and include pre-determined aspects, such as age and gender. In contrast, dynamic risk factors (e.g., attitudes toward drug use and criminal behavior) are amenable to change and serve as primary targets of successful interventions that reduce recidivism risk (Bonta & Andrews, 2007). For this reason, dynamic factors are also commonly referred to as individual "needs."

The Need principle highlights the importance of correctional treatment programs targeting criminogenic needs, which are dynamic risk factors (contrasted with static factors) that are directly associated with an individual's criminal behavior. According to Bonta and Andrews (2007), there are seven dynamic criminogenic risk factors that justice agencies should seek to target in treatment: antisocial personality patterns, pro-criminal attitudes, social supports for crime, substance use, family/marital relationships, school/work, and prosocial recreational activities. Of primary importance is the understanding that CJ agencies must not only assess for a person's risk of reoffending, but also their needs and unique characteristics that may act as a buttress or hindrance in certain types of treatment programs. Successful programming acknowledges the human capacity for change, which can be facilitated by appropriate interventions.

The Responsivity principle describes how treatment should be provided, considering both static (risk) factors and dynamic (need) factors. This principle highlights the necessity for both general and specific responsivity. General responsivity encompasses broader cognitive social learning strategies deemed effective across all types of CJ populations, maintaining that they conform to both the relationship principle and structuring principle (Bonta & Andrews, 2007). The relationship principle underscores the importance of counselor rapport and a therapeutic alliance characterized by a warm, respectful, and collaborative relationship between clients and counselors (Bonta & Andrews, 2007). The structuring principle describes how cognitive social learning strategies can change antisocial behavior via, for example, prosocial modeling, reinforcement protocols, and problem solving (Dowden & Andrews, 2004). Alternatively, specific responsivity comprises the adjustments made to an intervention so that it is better tailored to unique individuals (Bonta & Andrews, 2007). These modifications are made to account for a person's strengths, personality, learning style, and bio-social characteristics (e.g., sex/gender, race, age, education).

The RNR model is widely utilized by CJ agencies and has been successfully implemented in programs designed for incarcerated adults, juveniles, and community supervision agencies. The RNR model has been shown to be robust across many different justice-involved groups, including women (Blanchette & Brown, 2006; Dowden & Andrews, 1999a), those with mental health disorders (Andrews et al., 2001; Bonta et al., 1998), impoverished and financially stable individuals (Andrews et al., 2001), juveniles (Dowden & Andrews, 1999b), sex offenders (Hanson & Morton-Bourgon, 2007), and Aboriginal persons (Rugge, 2006).

Despite its apparent robustness and wide use among CJ agencies, the RNR model has been criticized, most notably for its lack of focus on individual strengths (e.g., Good Lives Model; see Brookes, 2010). Some researchers argue that harnessing individual strengths would necessitate a paradigm shift within the field of CJ, including assessment procedures and measures (Kazemian, 2021). Rather than focusing exclusively on criminogenic needs, some point to the need to treat each person individually and focus on providing opportunities (as opposed to threats and punishments). Critics commonly point out that the environmental context of imprisonment is aversive by design, and the negative impacts of imprisonment may unintentionally increase the possibility of recidivism more so than if someone does not experience incarceration (i.e., custodial sentences, longer sentences, and more punitive conditions of confinement may increase crime in the long run; Kazemian, 2021). Moreover, imprisonment has negative effects on other core life-course outcomes, such as employment opportunities, health and well-being, and family stability (Wildeman, 2021). Taken together, this suggests that incarceration may inhibit desistance on average. For this reason, some have argued that programs should focus on mitigating the negative aspects of the condition of imprisonment (e.g., nutrition, exercise, sleep, prosocial interactions, limiting noise pollution, limiting toxin exposure, and overcrowding; Boisvert, 2021). Further, some believe programs should also target neuropsychological deficits via cognitive remediation, mindfulness training, nutritional supplements, and medications for substance use and mental illness (Bucklen, 2021).

In summary, of primary concern according to the RNR model is the identification of individuals at high-risk for reoffending (Risk principle) and criminogenic needs that may be targeted in treatment (Need principle), and then using this information to inform how best to treat individual clients (Responsivity principle). Compared to CJ programs where people do not receive any treatment, programs that adhere to all three RNR principles have recidivism rates 17% lower when delivered in custodial settings and 35% lower when delivered in community settings (Andrews & Bonta, 2016). The current study relies on the principles of the RNR model to inform and guide analyses and examines risk level and treatment to determine if intensive treatment for high-risk individuals has a differential effect on recidivism rates when compared to those who did not receive treatment and to those in a low-risk grouping. Additionally, this project identifies reliable proxies/measures of criminogenic needs that successfully predict recidivism trends over long periods of time above and beyond static risk factors. Findings inform assessment practices within the field and protocols for selecting who will benefit most from intensive treatment services.

Current Study

First, this investigation assessed the predictive utility of three factors and how they are associated with post-release recidivism: (1) treatment (Therapeutic Community vs. Controls), (2) risk classification (High vs. Low), and (3) aftercare (Completed vs. Discontinued). In the original examination of the dataset, Knight et al. (1999) reported that individuals released from the therapeutic community were equally likely to return to custody within 3 years as those in the control group (41% vs. 42%, respectively). To allow for full processing of records and the longest possible follow-up window, the current study explored differences in post-release recidivism trajectories between treated and untreated groups over a 25-year follow-up period.

Results using updated records were expected to confirm previous findings. **H1a** tested whether treatment receipt was associated with a significantly longer time to rearrest compared to the control group. The lack of treatment effect reported by Knight et al. (1999) was attributed to the sampling bias in that individuals released from the treatment program were more likely to be classified as high risk compared to controls. Therefore, it was hypothesized that trajectories between the treated and untreated groups would vary according to risk level: high-risk individuals would have a longer time to rearrest if they received treatment compared to no treatment; in contrast, low-risk individuals would have a shorter time to rearrest if they received treatment compared to those who did not (**H1b**). This was based on the RNR model in which the Responsivity principle highlights the need to match treatment programming based on individuals' need for treatment (Bonta et al., 2000).

Similarly, the current study assessed how aftercare completion affected post-release recidivism trajectories over 25 years. Based on previous research on the effectiveness of aftercare programs (e.g., Galassi et al., 2015; Wexler & Prendergast, 2010), it was hypothesized that among in-prison treatment recipients, aftercare completion would extend the amount of time to first rearrest when compared to those who did not complete aftercare (**H2a**). Within risk levels, high-risk aftercare dropouts were expected to experience rearrest sooner than those who completed aftercare, regardless of risk classification; it was also hypothesized that there would be no difference between high-risk aftercare completers and low-risk participants regardless of aftercare completion (**H2b**).

The second objective was to establish a predictive algorithm of reincarceration patterns. The outcome variable was number of days spent incarcerated per year. Predictors included static factors (age, number of prior arrests, race, ethnicity, and risk classification), group (Control vs.

Aftercare Complete vs. Aftercare Discontinued), and proxies for five criminogenic needs (antisocial personality patterns, pro-criminal attitudes, social supports for crime, substance use, and family relationships). It was hypothesized that including criminogenic needs in the prediction of reincarceration patterns would account for greater variance than static factors alone (**H3**). The multilevel analyses were expected to provide insight into factors that can be targeted during treatment to improve outcomes. See Analytic Plan for variables within each level of the multilevel model.

Method

Sample

The initial sample consisted of 394 male participants incarcerated in Texas between June 10, 1993, and January 31, 1994 who originally consented to participate in the study (see Knight et al., 1999). When criminal records were updated for purposes of the present study, three ID numbers could not be linked back to the original participants. For that reason, the current study only includes 391 participants. Of those, 290 completed an in-prison therapeutic community program. The remaining 101 served as an untreated comparison sample recruited from the general prison population who were recommended by institutional staff to be sent to the in-prison therapeutic community during the same timeframe, but ultimately did not receive treatment because they were due to be released in less than 10 months or because of other Parole Board considerations. The final analytic dataset replaced the participant state identifier with a study identifier to protect participant confidentiality. There were no differences between the therapeutic community and untreated comparison groups in average age, race/ethnicity, education, or previous criminal offenses for robbery, burglary, or larceny. However, the treatment group was composed of a significantly higher number of participants with a previous drug offense (therapeutic community = 38%, untreated = 27%; $\chi^2 = 4.00$, $p < .05$) and a significantly higher number who were classified as high risk for recidivism (therapeutic community = 77%, untreated = 56%; $\chi^2 = 15.97$, $p < .01$; see Knight et al., 1999). Despite recruiting from the same pool of justice-involved people eligible for the therapeutic community, these differences indicate that the Parole Board tended to select more severe cases for treatment.

The treatment group can be further divided into whether participants completed community-based aftercare treatment after they were released. Of the 290 therapeutic community graduates, 169 completed aftercare treatment (3 months of community-based residential treatment followed by 1 to 12 months of community outpatient care). The remaining 121 either discontinued aftercare prior to completion, were expelled due to rule violations, or had their aftercare treatment extended beyond 6 months because of rule violations. Again, according to results published in Knight et al. (1999), these groups did not differ from each other or the untreated comparison group in terms of average age, race/ethnicity, education, or previous criminal offenses for robbery, burglary, or larceny. However, both aftercare completers (73%) and non-completers (83%) had significantly more participants classified as high risk compared to untreated comparisons [56%, $F(2, 391) = 10.15$, $p < .01$]; aftercare completers and dropouts were not significantly different from each other in this regard.

Procedure

Full procedural and recruitment details are described in Knight et al. (1999). For purposes of the present study, criminal records for the sample of 391 participants were analyzed and coded to evaluate criminal histories in the 25 years since data were initially collected (approximately 1994-2019). Seventy-six participants were confirmed as deceased before the end of the 25-year follow-up period. These data were collected through Ancestry.com, which provided information on exact dates of deaths based on state records and obituary searches. As a result, 315 participants have updated arrest and reincarceration histories for the full 25-year period following initial discharge date.

Criminal records were originally pulled from Texas Department of Criminal Justice (TDCJ), including reincarceration data in the three years following discharge (see Knight et al., 1999), up to 10 years post-release. For purposes of the present study, records were updated using criminal records available from Texas Department of Public Safety (TX DPS). The TX DPS records were used to code information on arrest history pre- and post-release, as well as incarceration history over the 25 years post-release (intake and discharge dates). Due to the reliance on Texas records, any arrests or incarcerations that occurred outside of Texas were unknown.

Measures

Sociodemographic Information

Demographic information was previously abstracted from the TDCJ Institutional Division database, and available information was confirmed using TX DPS record data. Information to be analyzed includes age, race, ethnicity, criminal history, and risk scores.

Mortality

Each participant was searched using Ancestry.com, relying on data available in TX DPS and TDCJ records, for dates of death. Ancestry.com was able to quickly search available state records (including records from the entirety of the United States) and obituaries to provide exact dates of death for participants. Additionally, participants who died while incarcerated in the state of Texas had dates of death within TX DPS records.

Risk Level

Risk level was extracted from TDCJ records of Salient Factor Scores, which measure the severity of an individual's crime and substance use problems. The measure of Salient Factor Scores was developed in the 1970s by the U.S. Parole Commission as a way of estimating an incarcerated individual's likelihood of recidivating following release from prison (Hoffman, 1994). Scores are a composite of nine items, five of which measure criminal history and four items assessing substance use disorders, education, previous employment, and plans for employment post-release. Total scores range from 0 (*highest risk/severity*) to 15 (*lowest risk/severity*). Total scores can then be converted such that scores ranging from 0-7 are categorized as "high risk" and scores ranging from 8-15 indicate an individual is "low risk." Higher risk people generally require intensive supervision because of their relatively severe crime and substance use problems, whereas low risk people need less supervision because their problems are less severe.

Criminogenic Needs

Proxies for five dynamic criminogenic needs were selected from available baseline measurements. The criminogenic needs analyzed in this study include family relationships, pro-criminal attitudes, antisocial personality pattern, substance use, and social supports for crime, (see Table 1 for list of criminogenic needs, indicators, and baseline measurements used to assess each dynamic factor).

Family relationships were assessed using self-reported number of family members the participant regularly stays in touch with, collected as part of the Brief Background Assessment (BBA; Simpson, 1991) administered to participants. Pro-criminal attitudes were assessed using self-reported amount of money made from illegal activities per week prior to incarceration as part of the BBA. A measure of risk-taking collected as part of the TCU Self-Rating Form's Psychosocial Functioning Scales (Knight et al., 1998; Simpson & Joe, 1993) at baseline was used to assess antisocial personality patterns. Items were rated on a 7-point Likert scale (1 = *Disagree Strongly*, 4 = *Uncertain*, 7 = *Agree Strongly*). Total scores for the risk-taking scale were calculated by averaging responses to relevant items. Substance use was measured via the TCU Alcohol Form (Simpson, 1991), specifically whether the participant was diagnosed with alcohol dependency based on criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders 3rd ed., revised (DSM-III-R; American Psychiatric Association, 1987). Scores were calculated according to guidelines in Chatham et al. (1995) to indicate whether participants could be considered alcohol dependent (Yes vs. No). A measure of alcohol use was intentionally selected over more general measures of substance use to prevent potential multicollinearity problems with risk scores, since Salient Factor Scores already account for substance use problems. Finally, how often their friends engaged in illegal activities served to measure social support for crime. This information was collected as part of the TCU Self-Rating Form (Knight et al., 1998; Simpson & Joe, 1993). Response options were presented on a 5-point Likert scale (0 = *Never*, 1 = *Rarely*, 2 = *Sometimes*, 3 = *Often*, 4 = *Always*).

Table 1

Measures of Criminogenic Needs

Criminogenic Need	Indicators	Measure Used
Family relationships	Poor family relationships	Number of family members who regularly stay in touch
Pro-criminal attitudes	Rationalizations for crime, negative attitudes towards the law	Amount of money made illegally per week

Table 1 (continued)

Criminogenic Need	Indicators	Measure Used
Antisocial personality pattern	Impulsive, adventurous, pleasure-seeking	Risk-taking
Substance abuse	Abuse of alcohol and/or drugs	Alcohol dependence
Social supports for crime	Criminal friends, isolation from prosocial others	Involvement with friends who engage in illegal activities

Note. This table is a modification of a table published in Bonta and Andrews (2007).

Recidivism

Recidivism information were coded from TX DPS and TDCJ records. Records from TX DPS were analyzed over the 25 years since participants were first released from prison following recruitment (approximately 1994 to 2019). Records from TDCJ were available for 10 years post-release (approximately 1994 to 2004). The present study relied on both rearrest and reincarceration rates. Arrest information included date of arrest, offense(s), and severity of offense (i.e., misdemeanor vs. felony). Reincarceration data included intake and discharge dates, as well as information on offense(s) for which the person was incarcerated (e.g., type of offense, new offense vs. parole revocation), although this information was not always clear. As a result, offense types and offense severity were not analyzed in the current study.

Analytic Plan

First, descriptive statistics were computed, including absolute recidivism rates and average length of time to first recidivism event (both rearrest and reincarceration). Twenty-five-year recidivism (rearrest and reincarceration) rates were calculated for the entire sample, and then examined by treatment receipt (Treatment vs. Controls), risk level (High vs. Low), and aftercare (Completed vs. Discontinued). Rates for both rearrest and reincarceration were disaggregated into follow-up intervals to assess changes in recidivism risk over time (post-release years 1, 3, 5, 10, 15, 20, 25).

The effect of treatment receipt was assessed by plotting Kaplan-Meier survival curves and comparing the difference in survival times between groups (Treatment vs. Controls) using a Breslow test (also known as the generalized Wilcoxon test or the Gehan Test; Breslow, 1970; Gehan, 1965). The Breslow test was used for group comparisons because it weights the differences according to the number of people at risk at each time point (i.e., those individuals at each time point that have not yet had the event occur – that is, rearrest). This type of weighting puts greatest emphasis on the differences between observed and expected events at earlier rather than later time points when calculating the test statistic (Laerd Statistics, 2015). As rearrest rates were expected to be most dissimilar shortly after release, with any differences gradually disappearing over time, the Breslow test was most appropriate. The Breslow test examined the null hypothesis that there was no difference in the overall survival distributions between groups in the population. Participants who died during the 25-year follow-up period were censored.

The first objective of this study was to confirm previous findings (see Knight et al., 1999) using updated records. Specifically, **H1a** tested whether people who received treatment ($n = 290$) had a significantly longer amount of time to first rearrest compared to controls ($n = 101$). To test the interactions between risk and treatment, a Cox regression was performed. This analysis compared the hazard ratios of treatment groups (Treatment vs. Controls) while accounting for risk (High vs. Low). The hazard ratio indicates the probability of reaching the endpoint (i.e., rearrest) at time point, i, given that the individual has not reached it up to that point (De Neve & Gerds, 2020). Based on the Responsivity principle of the RNR model, it was hypothesized (**H1b**) that high-risk individuals would have a shorter time to rearrest if they did not receive treatment compared to if they did receive treatment. Analyses also explored the hypothesis that low-risk people would have a shorter time to rearrest if they received treatment compared to if they did not. Risk and treatment receipt were dummy-coded (0 = High Risk-Treatment) to predict time to first rearrest. To examine all possible comparisons, analyses were re-run two more times with Low Risk-Control and High Risk-Control serving as the comparison groups.

The effect of aftercare completion was assessed by plotting Kaplan-Meier survival curves and comparing the difference in survival times between groups (Completed vs. Discontinued) using a Breslow test. **H2a** tested whether people who completed aftercare (n = 169) had a significantly longer amount of time to first rearrest compared to those who did not complete aftercare (n = 121). A second Cox regression tested the hypothesis (**H2b**) that, among in-prison treatment recipients, high-risk individuals who did not complete aftercare would have a shorter time to rearrest compared to aftercare completers. Aftercare completers classified as high risk were not expected to be different from low-risk participants, regardless of aftercare completion status. Risk and aftercare completion were dummy-coded (0 = High Risk-Completed) to predict time to first rearrest. To examine all possible comparisons, analyses were re-run two more times with Low Risk-Discontinued and High Risk-Discontinued serving as comparison groups. Again, deaths were censored over the 25-year follow-up period.

To evaluate **H3**, a 2-stage multilevel model established the strongest predictive algorithm of number of reincarcerations over 25 years using full maximum likelihood method of estimation. The dependent variable was the number of days spent incarcerated per year. Level-2 included static factors (age, number of prior arrests, race, ethnicity, risk), criminogenic needs (number of family members regularly stayed in touch with, amount of money earned illegally per week, risk-taking, alcohol dependence, pro-criminal friends), and whether they completed aftercare, did not complete aftercare, or were part of the control group (dummy-coded: 0 = Aftercare Completed). All continuous Level-2 variables were grand mean centered prior to being entered into the model. It was hypothesized that including criminogenic needs in the prediction of reincarceration patterns would account for greater variance than static factors alone (**H3**). After all variables had been added to the model, non-significant variables were removed one level at a time until only significant predictors remain (i.e., quadratic term first, then linear term, then intercept last). Since the analysis was exploratory, the cutoff for determining significance was $p = .10$. Hox (1998) recommends a minimum of 20 Level-1 observations for 50 Level-2 individuals when examining cross-level interactions. There was a sufficient sample size in the present study (Level-1 time points = 25; Level-2 minimum $n = 94$) and thus analyses are adequately powered.

Level-1: Number of days spent incarcerated; Time (Linear); Time^2 (Quadratic)

Level-2: Static factors; Criminogenic needs (dynamic factors); Group (aftercare discontinued vs. controls vs. aftercare completed)

Results

Descriptive Statistics

After removing three participants from the original dataset because their state ID numbers could not be verified, the final sample consisted of 391 males released from either the general prison population (Controls; $n = 101$, 26%) or an in-prison therapeutic community (Treatment; $n = 290$, 74%) in Texas in 1994 (see Table 2 for summary of descriptive statistics). The majority of the sample was classified as high risk for recidivism based on Salient Factor Scores (high risk: $n = 281$, 72%; low risk: $n = 110$, 28%). Of those released from the therapeutic community, 169 (58%) completed the aftercare program, and 121 (42%) were classified as non-completers because they dropped out before completing aftercare or had their aftercare extended beyond 6 months due to rule violations.

Table 2

Background Characteristics

Variables	Aftercare Completed (*n* = 169)	Aftercare Discontinued (*n* = 121)	Controls (*n* = 101)
Race			
Black	82 (48.5%)	51 (42.1%)	44 (43.6%)
White	87 (51.5%)	70 (57.9%)	57 (56.4%)
Ethnicity			
Hispanic	33 (19.5%)	31 (25.7%)	18 (17.8%)
Non-Hispanic	136 (80.5%)	90 (74.4%)	83 (82.2%)
Risk Classification			
Low	39 (23.1%)	27 (22.3%)	44 (43.6%)
High	130 (76.9%)	94 (77.7%)	57 (56.4%)
Death			
No	134 (79.3%)	97 (80.2%)	84 (83.2%)
Yes	35 (20.7%)	24 (19.8%)	17 (16.8%)

Note. Numbers represent counts (and percentages).

Criminal records indicated the participants were either Black (*n* = 177, 45%) or White (*n* = 214, 55%), and 82 participants were Hispanic (21%). Seventy-six (19%) participants died at some point during the 25-year follow-up period. Chi-square tests of independence were conducted between group (Controls vs. Aftercare Discontinued vs. Aftercare Completed) and race, ethnicity, risk classification, and mortality. All expected cell frequencies were greater than five. Group was not significantly associated with race, $\chi^2(2) = 1.32$, $p = .518$, ethnicity, $\chi^2(2) = 2.40$, $p = .302$, or mortality, $\chi^2(2) = 0.63$, $p = .732$. There was a significant association between group and risk level, $\chi^2(2) = 16.06$, $p < .001$. The effect size was small (Cohen, 1988), Cramer's V = .203. Table 3 presents frequencies and adjusted standardized residuals. Residual values greater than three indicate the cell deviates from independence (Agresti, 2007; Agresti, 2013; Agresti & Franklin, 2014).

Table 3

Crosstabulation of Group and Risk Classification

	Group		
Risk Classification	Aftercare Completed (*n* = 169)	Aftercare Discontinued (*n* = 121)	Controls (*n* = 101)
Low Risk	39 (-1.9)	27 (-1.7)	44 (4.0)
High Risk	130 (1.9)	94 (1.7)	57 (-4.0)

Note. Adjusted residuals appear in parentheses below observed frequencies.

Of all 391 participants, 332 (85%) were rearrested at least once in the 25 years post-release (see Table 4 for rearrest rates disaggregated into post-release years 1, 3, 5, 10, 15, 20, and 25). The average number of days between participants' original discharge dates and the date of their first arrest was 1,313 days (*SD* = 1553.93, Range = 0-10172), or about 3 years and 7 months. Within risk classification, 246 high-risk participants (88%) and 86 low-risk participants (78%) were rearrested at least once. High- ($M = 1223.00$, $SD = 1453.02$) and low-risk ($M = 1570.62$, $SD = 1796.41$) groups did not differ with regard to number of days to first rearrest, $t(126.04) = 1.62$, $p = .108$ (note degrees of freedom adjusted due to inequality of variances). However, trends suggest the plateau period may occur earlier for high-risk individuals (Year 10) compared to those who are low risk (Year 15). Of those released from the therapeutic community, 247 (85%) were rearrested; among the control group, 85 (84%) were rearrested at least once. The treatment (*M* = 1247.93, *SD* = 1485.25) and control (*M* = 1502.27, *SD* = 1733.81) groups did not significantly differ in terms of number of days to first rearrest, *t*(330) = 1.30, *p* = .194. An independent samples t-test showed that, within the control group, low-risk individuals (*M* = 1996.91, *SD* = 2187.03) had significantly more days between their initial discharge date and first rearrest compared to high-risk individuals (*M* = 1188.37, *SD* = 1300.48), *t*(83) = 2.139, *p* = .035. Within the treatment group, 140 aftercare completers (83%) and 107 non-completers (88%) were rearrested. The difference between aftercare completers (*M* = 1407.34, *SD* = 1660.41) and non-completers (*M* = 1039.36, *SD* = 1194.46) in number of days to rearrest was not significant, *t*(245) = 1.94, *p* = .054. Independent samples *t*-tests showed that differences between high- and low-risk groups were not significant within aftercare discontinued, *t*(105) = 0.03, *p* = .978, or aftercare completed groups, *t*(138) = 0.34, *p* = .731.

Table 4

Rearrest Rates by Risk Level Classification

Group	Year 1	Year 3	Year 5	Year 10	Year 15	Year 20	Year 25
Control (*n* = 101)							
Low Risk (n = 44)	9 (20.5%)	16 (36.4%)	21 (47.7%)	26 (59.1%)	30 (68.2%)	32 (72.7%)	33 (75.0%)
High Risk (n = 57)	18 (31.6%)	32 (56.1%)	39 (68.4%)	50 (87.7%)	52 (91.2%)	52 (91.2%)	52 (91.2%)

Table 4 (continued)

Group	Year 1	Year 3	Year 5	Year 10	Year 15	Year 20	Year 25
Discontinued Aftercare (n = 121)							
Low Risk (n = 27)	8 (29.6%)	16 (59.3%)	17 (63.0%)	20 (74.1%)	22 (81.5%)	22 (81.5%)	22 (81.5%)
High Risk (n = 94)	37 (39.4%)	57 (60.6%)	67 (71.3%)	82 (87.2%)	85 (90.4%)	85 (90.4%)	85 (90.4%)
Completed Aftercare (n = 169)							
Low Risk (n = 39)	7 (17.9%)	17 (43.6%)	22 (56.4%)	29 (74.4%)	30 (76.9%)	31 (79.5%)	31 (79.5%)
High Risk (n = 130)	27 (20.8%)	67 (51.5%)	83 (63.8%)	101 (77.7%)	104 (80.0%)	107 (82.3%)	108 (82.3%)

Note. Numbers represent counts (and percentages).

Participants were arrested, on average, 4.48 (SD = 4.59) additional times after they were released following recruitment into the study. The average number of rearrests within the treatment group (M = 4.41, SD = 4.38) was similar to observed rates in the control group (M = 4.67, SD = 5.15), $t(389) = 0.49$, $p = .625$. There were slightly more rearrests among those who did not complete aftercare (M = 4.98, SD = 4.42) when compared to those who did (M = 4.01, SD = 4.33), although this difference was not statistically significant, $t(288) = 1.85$, $p = .065$. Notably, high-risk participants (M = 4.83, SD = 4.75) were rearrested significantly more times than the low-risk participants (M = 3.60, SD = 4.02), $t(389) = 2.39$, $p = .017$. As one might expect, those who died (M = 2.64, SD = 3.03) during the 25-year follow-up period were arrested significantly fewer times than those who did not (M = 4.92, SD = 4.79), $t(177.04) = 5.18$, $p < .001$, underscoring the importance of censoring in subsequent survival analyses.

Table 5

Reincarceration Rates by Risk Level Classification

Group	Year 1	Year 3	Year 5	Year 10	Year 15	Year 20	Year 25
Control (*n* = 101)							
Low Risk (n = 44)	5 (11.4%)	21 (47.7%)	25 (56.8%)	28 (63.6%)	34 (77.3%)	34 (77.3%)	35 (79.5%)
High Risk (n = 57)	11 (19.3%)	37 (64.9%)	43 (75.4%)	48 (84.2%)	49 (86.0%)	49 (86.0%)	51 (89.5%)
Discontinued Aftercare (*n* = 121)							
Low Risk (n = 27)	4 (14.8%)	17 (63.0%)	18 (66.7%)	21 (77.8%)	22 (81.5%)	22 (81.5%)	22 (81.5%)
High Risk (n = 94)	18 (19.1%)	63 (67.0%)	74 (78.7%)	80 (85.1%)	85 (90.4%)	86 (91.5%)	86 (91.5%)
Completed Aftercare (*n* = 169)							
Low Risk (n = 39)	5 (12.8%)	13 (33.3%)	18 (46.2%)	24 (61.5%)	24 (61.5%)	25 (64.1%)	25 (64.1%)
High Risk (n = 130)	14 (10.8%)	67 (51.5%)	89 (68.5%)	99 (76.2%)	104 (80.0%)	107 (82.3%)	107 (82.3%)

Note. Numbers represent counts (and percentages).

A total of 326 participants (83%) were reincarcerated at least once during the 25-year follow-up period (see Table 5 for reincarceration rates at years 1, 3, 5, 10, 15, 20, and 25 of the study). The average number of days between initial discharge date and first reincarceration date was 1,236 days (*SD* = 1403.21, Range = 0-8925), or about 3 years and 5 months. Within risk classification, 244 high-risk participants (87%) and 82 low-risk participants (75%) were reincarcerated at least one time. Eighty-six participants (85%) in the control group and 240 (83%) in the treatment group were reincarcerated. Within the treatment group, 132 aftercare completers (78%) and 108 non-completers (89%) experienced a reincarceration event.

Independent samples *t*-tests showed that differences in number of days between initial discharge and first reincarceration among high- and low-risk individuals were not significant within the control, $t(84) = 1.13$, $p = .260$, aftercare discontinued, $t(106) = 0.24$, $p = .813$, or aftercare completed groups, $t(130) = 0.78$, $p = .438$.

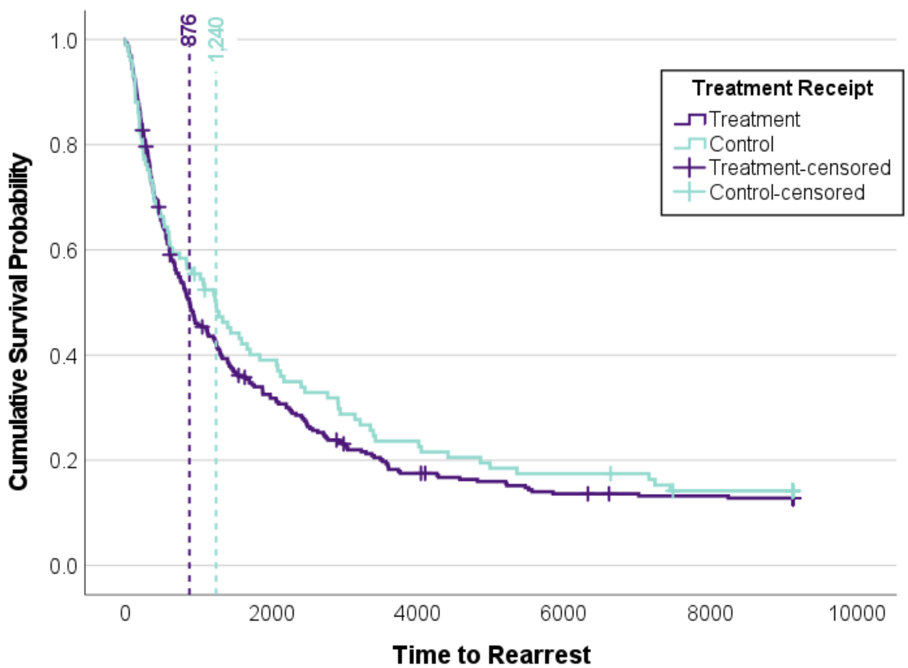
On average, participants spent 2,507 days (about 6 years and 10 months, $SD = 2145.25$, Range = 3-8834) incarcerated in the 25 years since they were first released from prison following recruitment. Individuals in the treatment group ($M = 2634.39$, $SD = 2214.68$) spent approximately 484 more days incarcerated, on average, over the 25 years post-release compared to those in the control group ($M = 2150.28$, $SD = 1905.42$), although this difference was not statistically significant, $t(172.81) = 1.93$, $p = .055$. Participants who did not complete aftercare ($M = 2685.87$, $SD = 2183.21$) spent, on average, about 94 additional days incarcerated compared to individuals who completed the aftercare program ($M = 2592.27$, $SD = 2247.51$), which was not a significant difference, $t(238) = 0.33$, $p = .745$. High-risk participants ($M = 2702.76$, $SD = 2216.76$) spent approximately 780 more days incarcerated than low-risk participants ($M = 1923.23$, $SD = 1806.33$), and this difference was statistically significant, $t(169.29) = 3.18$, $p = .002$.

Effect of Treatment Receipt

Participants were categorized based on whether they received treatment at the in-prison therapeutic community or not: Treatment ($n = 290$) or Control ($n = 101$). Kaplan-Meier survival analysis (Kaplan & Meier, 1958) was conducted to compare the two groups for their effectiveness at preventing rearrest. A similar percentage of censored cases was present in the Control (15.2%) and Treatment (15.8%) groups. As indicated in the plot of survival functions (Figure 1) participants that were in the Treatment group had a median time to rearrest of 876 days (approximately 2 years and 5 months), 95% CI [664.92, 1087.08]. This was shorter compared to the Control group, which had a median time to rearrest of 1240 days (approximately 3 years and 5 months), 95% CI [776.48, 1703.52]. The unexpected direction of this relationship may reflect differences in baseline risk scores (i.e., significantly more individuals classified as high risk in the Treatment group compared to the Control group). A Breslow test was run to determine if there were differences in the survival distribution for the Treatment and Control groups. The survival distributions for the two groups were not significantly different, $\chi^2(1) = 0.51$, $p = .476$.

Figure 1

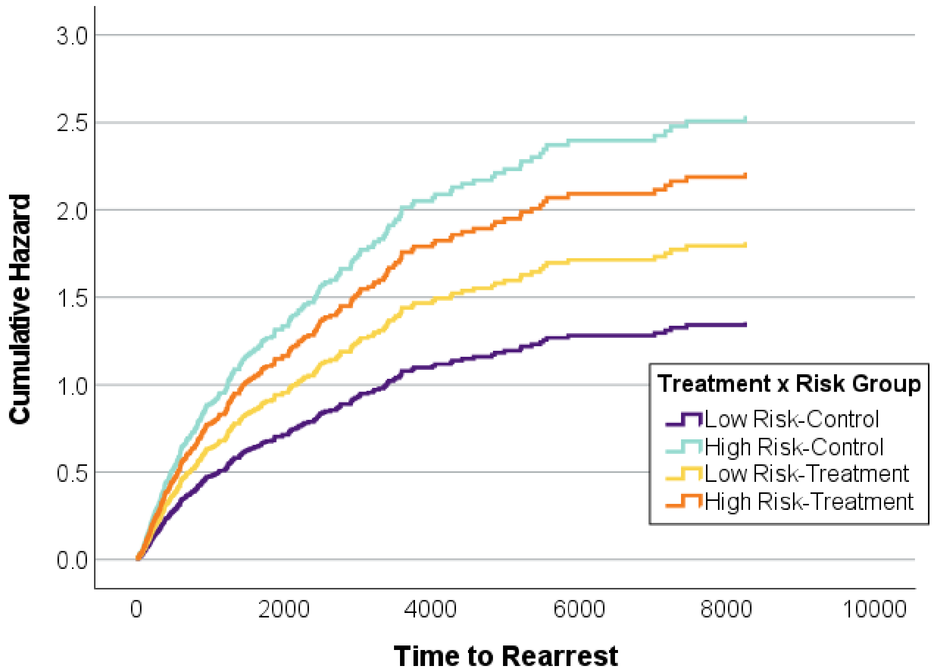
Kaplan Meier Survival Distributions: Treatment vs. Control Groups



Note. Dashed vertical lines indicate median number of days to rearrest for each group. Groups were not significantly different ($p = .476$).

Figure 2

Cox Regression Hazard Functions: Treatment Receipt x Risk



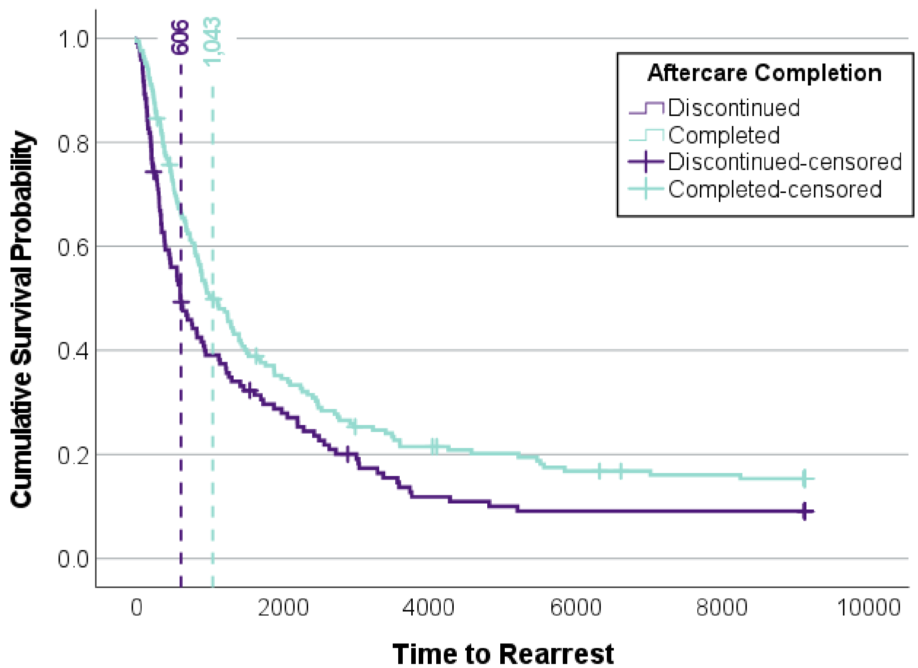
Note. Low Risk-Controls have a significantly lower hazard rate than both High Risk-Controls (p = .005) and High Risk-Treatment groups (p = .010).

A Cox Regression (see Figure 2) was conducted to compare the effects of treatment receipt (Treatment vs. Control) and risk classification (Low vs. High). Participants were classified into one of four groups (Low Risk-Control, High Risk-Control, Low Risk-Treatment, High Risk-Treatment), with High Risk-Treatment serving as the comparison group. The result of the likelihood ratio test suggests the model is a significant improvement in fit relative to the null, $\chi^2(3) = 10.49$, $p = .015$. While the High Risk-Treatment group was not significantly different from either the High Risk-Control (b = 0.14, SE = 0.16, p = .385) or the Low Risk-Treatment group (b = -0.20, SE = 0.16, p = .199). The hazard rate for rearrest was significantly higher in the High Risk-Treatment group compared to the Low Risk-Control group (b = -0.49, SE = 0.19, p =

.010). The hazard ratio for rearrest is 1.63 times more likely in the High Risk-Treatment group compared to the Low Risk-Control group (β = 0.61, 95% CI [0.42, 0.89]). The analysis was re-run with Low Risk-Controls serving as the reference group. While Low Risk-Controls were not significant different from the Low Risk-Treatment group (b = 0.29, SE = 0.22, p = .191), the hazard rate for rearrest was significantly lower compared to High Risk-Controls (b = 0.63, SE = 0.22, p = .005). The hazard ratio for rearrest suggests those in the High Risk-Control group were 1.87 times more likely to be rearrested compared to those in the Low Risk-Control group (β = 1.87, 95% CI [1.21, 2.90]). The analysis was re-run once more to compare High Risk-Controls against the Low Risk-Treatment group, with the results showing they were not significantly different (b = -0.34, SE = 0.20, p = .086).

Figure 3

Kaplan Meier Survival Distributions: Aftercare Completed vs. Discontinued



Note. Dashed vertical lines indicate median number of days to rearrest for each group. Groups were significantly different from each other (p = .003).

Effect of Aftercare Completion

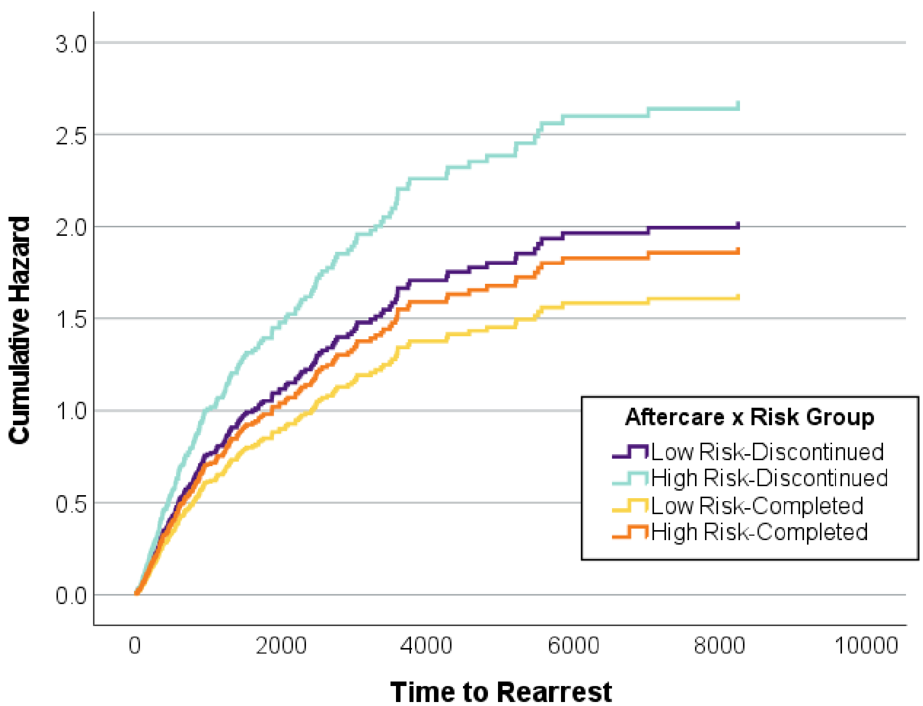
Participants were categorized based on whether they completed aftercare or not: Completed (*n* = 169) or Discontinued (*n* = 121). Kaplan-Meier survival analysis (Kaplan & Meier, 1958) was conducted to compare the two groups for their effectiveness at preventing rearrest. A similar percentage of censored cases was present in the Discontinued (11.6%) and Completed (17.8%) groups. Participants that were in the Completed group had a median time to rearrest of 1,043 days (approximately 2 years and 11 months), 95% CI [738.12, 1347.88]. This was longer compared to the Discontinued group, which had a median time to rearrest of 606 days (approximately 1 year and 8 months), 95% CI [434.54, 777.47]. A Breslow test was run to determine if there were differences in the survival distribution for the Completed and Discontinued groups. The survival distributions (see Figure 3) for the two groups were statistically significantly different, $\chi2(1) = 9.03$, $p = .003$. Specifically, those who completed the aftercare program avoided being rearrested for a significantly longer period of time post-release than those who did not complete the aftercare program.

A Cox Regression (see Figure 4) was conducted to compare the effects of aftercare completion (Discontinued vs. Completed) and risk classification (Low vs. High). Participants were classified into one of four groups (Low Risk-Discontinued, High Risk-Discontinued, Low Risk-Completed, High Risk-Completed), with High Risk-Completed serving as the comparison group. The result of the likelihood ratio test suggests the model is a significant improvement in fit relative to the null, $\chi^2(3) = 8.04$, $p = .045$. The High Risk-Completed group was not significantly different from either the Low Risk-Discontinued ($b = 0.07$, $SE = 0.23$, $p = .761$) or the Low Risk-Completed groups ($b = -0.14$, $SE = 0.20$, $p = .481$). However, the hazard rate for rearrest was significantly lower in the High Risk-Completed group compared to the High Risk-

Discontinued group (b = 0.35, SE = 0.15, p = .016). Among high-risk participants, the hazard ratio for rearrest is 1.42 times more likely when individuals do not complete aftercare compared to when they complete the aftercare program (β = 1.42, 95% CI [1.07, 1.89]). Next, the analysis was re-run with the Low Risk-Discontinued group serving as the reference. This group was not significantly different from either the High Risk-Discontinued (b = 0.28, SE = 0.24, p = .242) or the Low Risk-Completed (b = -0.22, SE = 0.28, p = .441) groups. When the analysis was re-run a final time to compare the High Risk-Discontinued group against the Low Risk-Completed group, the result was significant (b = -0.50, SE = 0.21, p = .018). The hazard ratio for rearrest is 1.64 times more likely for those in the High Risk-Discontinued group compared to the Low Risk-Completed group (β = 0.61, 95% CI [0.40, 0.92]).

Figure 4

Cox Regression Hazard Functions: Aftercare Completion x Risk



Note. High Risk-Discontinued group has significantly higher hazard rate than both Low Risk-Completed (p = .018) and High Risk-Completed (p = .016) groups.

Hierarchical Linear Model

Table 6 depicts descriptive statistics of the variables included in the original hypothesized model. During post-release Year 1, the mean age was 34.20 (*SD* = 8.83); the mean number of prior arrests was 7.67 (*SD* = 4.79); the mean number of family members respondents stayed in touch with regularly was 1.68 (*SD* = 8.59); the mean amount of money earned illegally per week was $420.55 (*SD* = $3,245.75); the mean risk-taking score was 1.11 (*SD* = 4.35); the mean score for the question asking whether the participant had friends who engaged in illegal activities was 0.44 (*SD* = 2.27). The average number of days incarcerated per year (Level-1) were as follows: 91.41 (*SD* = 145.78) at Year 1, 120.90 (*SD* = 153.23) at Year 3, 144.72 (*SD* = 165.44) at Year 5, 103.86 (*SD* = 150.14) at Year 10, 95.97 (*SD* = 147.50) at Year 15, 69.79 (*SD* = 134.37) at Year 20, and 68.12 (*SD* = 134.99) at Year 25. An examination of the residuals at both Level-1 and Level-2 confirmed that assumptions were met. Specifically, Level-1 residuals had a normal distribution with a constant variance, Level-2 residuals were independent from Level-1 residuals, and Level-2 residuals were independent between individuals.

Table 6

Hierarchical Linear Model: Descriptive Statistics

Variable	*n*	*M*	*SD*	Min	Max
Days Spent Incarcerated (Level-1)	8864	91.41	145.78	0.00	366.00
Year 1 (Time 0)	391	14.35	46.66	0.00	365.00
Year 2 (Time 1)	389	88.53	127.37	0.00	366.00
Year 3 (Time 2)	386	120.90	153.23	0.00	365.00
Year 4 (Time 3)	383	139.49	165.48	0.00	366.00
Year 5 (Time 4)	383	144.72	165.44	0.00	365.00

Table 6 (continued)

Variable	*n*	*M*	*SD*	Min	Max
Year 6 (Time 5)	379	131.88	168.30	0.00	366.00
Year 7 (Time 6)	376	120.27	160.39	0.00	365.00
Year 8 (Time 7)	372	106.51	155.26	0.00	365.00
Year 9 (Time 8)	369	106.63	154.36	0.00	365.00
Year 10 (Time 9)	363	103.86	150.14	0.00	366.00
Year 11 (Time 10)	362	98.42	146.90	0.00	365.00
Year 12 (Time 11)	360	94.48	142.26	0.00	365.00
Year 13 (Time 12)	354	92.74	149.62	0.00	365.00
Year 14 (Time 13)	349	91.40	147.62	0.00	366.00
Year 15 (Time 14)	346	95.97	147.50	0.00	365.00
Year 16 (Time 15)	344	89.20	143.14	0.00	365.00
Year 17 (Time 16)	341	80.99	139.73	0.00	365.00
Year 18 (Time 17)	339	75.97	136.36	0.00	366.00
Year 19 (Time 18)	336	67.07	130.80	0.00	365.00
Year 20 (Time 19)	330	69.79	134.37	0.00	365.00
Year 21 (Time 20)	325	64.60	129.31	0.00	365.00
Year 22 (Time 21)	323	64.13	129.95	0.00	366.00
Year 23 (Time 22)	322	65.26	132.25	0.00	365.00
Year 24 (Time 23)	321	65.46	133.21	0.00	365.00
Year 25 (Time 24)	321	68.12	134.99	0.00	365.00

Table 6 (continued)

Variable	*n*	*M*	*SD*	Min	Max
Level-2					
Age	391	34.47	7.73	19.73	63.60
Arrests	391	7.73	4.70	1.00	33.00
Family	104	6.38	5.97	0.00	30.00
Illegal Earnings	105	1578.05	2863.44	0.00	16000.00
Risk-taking	105	4.18	1.58	1.00	7.00
Pro-criminal Friends	94	1.85	1.38	0.00	4.00

Note. *M* = mean, *SD* = standard deviation, Min = minimum score, Max = maximum score.

Participant Attrition (Death)

As mentioned previously, 76 participants (19%) died at some point in the 25 years after they were initially released from prison. The average age at time of death was 53 years (SD = 10.29, Range = 31-75). Two participants died within the first year of release (Year 1), six died during Years 2-3, four died during Years 4-5, 17 died during Years 6-10, 18 died during Years 11-15, 19 died during Years 16-20, and 10 died during Years 21-25. The level for declaring statistical significance (i.e., $p < .05$) was adjusted to compensate for making multiple comparisons. A Bonferroni correction was made with statistical significance accepted at the $p < .004$ level. Independent *t*-tests showed that participants who died during the 25-year follow-up period were significantly older ($M = 39.75$, $SD = 9.45$) at the initial discharge date than those that did not ($M = 33.19$, $SD = 6.68$), $t(93.81) = 5.71$, $p < .001$ (note degrees of freedom adjusted for unequal variances). Additionally, those who died ($M = 9.22$, $SD = 5.44$) had significantly more prior arrests than those who did not ($M = 7.37$, $SD = 4.44$), $t(100.43) = 2.76$, $p = .002$.

However, neither age nor prior arrests was included in the final model. There were no significant differences in death rates for measures of pro-criminal friends (p = .028), risk-taking (p = .037), family relationships (p = .075), or illegal earnings (p = .634).

Chi-square tests for association were conducted between death (Yes vs. No) and treatment receipt (Treatment vs. Control), risk (Low vs. High), aftercare (Completed vs. Discontinued), race (White vs. Black), ethnicity (Hispanic vs. non-Hispanic), and alcohol dependence (Yes vs. No). All expected cell frequencies were greater than five. Death was not significantly associated with treatment receipt, $\chi^2(1) = 0.59$, $p = .442$, aftercare completion, $\chi^2(1) = 0.03$, $p = .855$, risk classification, $\chi^2(1) = 0.46$, $p = .499$, race, $\chi^2(1) = 7.14$, $p = .008$, ethnicity, $\chi^2(1) = 0.11$, $p = .739$, or alcohol dependence, $\chi^2(1) = 1.48$, $p = .223$.

Unconditional Model

Before analyzing the impact of any predictors, days incarcerated was analyzed in a 2-Level growth model in which observation occasions (Times 0-24; Level-1, n = 8,864) were nested within the individual level (Level-2, n = 391). An unconditional model was run to test if there was variability within individuals and between individuals in the dependent outcome that the predictors could explain, and the intraclass correlation (ICC) was calculated for measuring the ratio of the between-individual variance to the total variance. The unconditional model of the 2-level HLM revealed that the ICC equaled 34%, meaning that 66% of the variance was within individuals and 34% of the variance was between individuals. The intercept of the unconditional model was significantly different from zero, $\beta_{00} = 90.82$, $SE = 4.52$, $t(390) = 20.11$, $p < .001$, indicating the average number of days incarcerated for all the participants across the 25-year follow-up was 91 days per year (see Model 1 in Table 7).

Unconditional Growth Model

Preliminary HLM analyses were conducted to identify the growth curve of days incarcerated at Level-1. In Model 2, the linear term was allowed to vary, and the quadratic term was fixed at Level-1 (see Equation 1 below).

$$\begin{aligned} Days\ Incarcerated_{ti} &= \pi_{0i} + \pi_{1i}(Linear_{1i}) + \pi_{2i}(Quadratic_{2i}) + e_{ti} \\ \pi_{0i} &= \beta_{00} + r_{0i} \\ \pi_{1i} &= \beta_{10} + r_{1i} \\ \pi_{2i} &= \beta_{20} \end{aligned} \tag{1}$$

In the Level-1 model above, days incarcerated for participant *i* at time *t* is equal to the intercept π_{0i} (mean days incarcerated at Year 0), plus the effect of slope π_{1i} (linear change in days incarcerated from one year to the next), plus the fixed effect of slope π_{2i} (quadratic change in days incarcerated from one year to the next), plus the residual error between predicted and observed scores at each observation time, e_{ti}. In the Level-2 model, the intercept π_{0i} for participant *i* is equal to the intercept β_{00} (mean number of days incarcerated across all participants), plus the between-person residuals on days incarcerated (r_{0i}). The slope of the linear term at Level-1 (π_{1i}) is equal to the intercept β_{10} (mean slope of linear change in days incarcerated across all participants), plus the between-person residuals on days incarcerated (r_{1i}). The slope of the fixed quadratic term at Level-1 (β_{20}) is equal to the intercept β_{20} (mean slope of quadratic change in days incarcerated across all participants). The HLM model results (see Model 2 in Table 7) indicated that the intercept was significantly different from zero, β_{00} = 91.30, *SE* = 5.84, *t*(390) = 15.64, *p* < .001. The slope of the linear term was significant, β_{10} = 3.93, *SE* = 1.15, *t*(390) = 3.42, *p* < .001, and the slope of the quadratic term was also significant, β_{20} = -0.26, *SE* = 0.05, *t*(8081) = -5.58, *p* < .001, suggesting that for each additional year post-release, days incarcerated increased by about 4 days, and the rate of increase decreased by 0.26 days.

In Model 3 (see Table 7), both the linear and quadratic terms were allowed to vary (see Equation 2 below).

$$Days\ Incarcerated_{ti} = \pi_{0i} + \pi_{1i}(Linear_{1i}) + \pi_{2i}(Quadratic_{2i}) + e_{ti}$$

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i} \qquad (2)$$

$$\pi_{2i} = \beta_{20} + r_{2i}$$

The Level-1 model equation, as well as the equations for the intercept (π_{0i}) and linear slope (π_{1i}), are the same as for Equation 1. The slope of the quadratic term at Level-1 (π_{2i}) is equal to the intercept β_{20} (mean slope of quadratic change in days incarcerated across all participants) plus the between-person residuals on days incarcerated (r_{2i}).

The third HLM model revealed that the intercept was significantly different from zero, β_{00} = 91.44, *SE* = 5.80, *t*(390) = 15.77, *p* < .001, and the slope of both the linear and quadratic terms were significant: β_{10} = 3.92, *SE* = 1.13, *t*(390) = 3.48, *p* < .001; β_{20} = -0.26, *SE* = 0.04, *t*(390) = -5.68, *p* < .001, respectively. The results suggest that as the amount of time post-release increases one year, days incarcerated increases by 4 days, but the rate of increase decreased 0.26 days.

The deviance test indicated that the HLM model with the fixed quadratic slope at Level-1 fit the data better than the empty model, $\chi^2(4) = 1143.65$, *p* < .001, and the random quadratic growth curve fit the data better than the fixed quadratic term, $\chi^2(3) = 545.12$, *p* < .001. The growth model revealed significant variation in the Year 1 number of days incarcerated (*Var* = 9890.67, *df* = 385, χ^2 = 1519.10, *p* < .001), the linear slope among participants (*Var* = 353.14, *df*

= 385, χ^2 = 1596.05, p < .001), and the quadratic slope among participants (*Var* = 0.54, *df* = 385, χ^2 = 1548.19, p < .001; see Model 3 in Table 7).

Table 7

Models 1-3: Unconditional Model, Fixed Growth Model, and Random Growth Model

Fixed Effect	Model 1		Model 2		Model 3	
	π	*SE*	π	*SE*	π	*SE*
Intercept, β_{00}	90.82	4.52	91.30	5.84	91.44	5.80
Linear Slope, β_{10}			3.93	1.15	3.92	1.13
Quadratic Slope, β_{20}			-0.26	0.05	-0.26	0.04
Random Effect	Estimate		Estimate		Estimate	
Within-person, e_{ti}	13,909.34		11,304.17		10,063.42	
Intercept, r_{0i}	7,240.34		10,948.79		9,890.67	
Linear Slope, r_{1i}			44.32		353.14	
Quadratic Slope, r_{2i}					0.54	
Deviance (parameters)	110,697.72 (3)		109,554.07 (7)		109,008.95 (10)	

Note. SE = standard error. All coefficients are significant (p < .001).

Model 1 = Unconditional Model
Model 2 = Equation 1
Model 3 = Equation 2

Static Factors

In the static factor model, the following variables were added at Level-2 to test their impact on the initial level and the rate of change in days incarcerated: age at initial discharge date (grand mean centered), number of prior arrests (grand mean centered), race (dummy-coded: White = 0, Black = 1), ethnicity, (dummy-coded: non-Hispanic = 0, Hispanic = 1), risk classification (dummy-coded: Low = 0, High = 1), and group (dummy-coded: Aftercare Completed = 0). The general static factor model equation (Equation 3) is as follows:

$$Days\ Incarcerated_{ti} = \pi_{0i} + \pi_{1i}(Linear_{1i}) + \pi_{2i}(Quadratic_{ti}) + e_{ti}$$

$$\mu_{0i} = \beta_{00} + \beta_{01}(Age) + \beta_{02}(Arrests) + \beta_{03}(Race) + \beta_{04}(Ethnicity) +$$
$$\beta_{05}(Risk) + \beta_{06}(Controls) + \beta_{07}(Discontinued) + r_{0i} \quad (3)$$
$$\mu_{1i} = \beta_{10} + \beta_{11}(Age) + \beta_{12}(Arrests) + \beta_{13}(Race) + \beta_{14}(Ethnicity) +$$
$$\beta_{15}(Risk) + \beta_{16}(Controls) + \beta_{17}(Discontinued) + r_{1i}$$
$$\mu_{2i} = \beta_{20} + \beta_{21}(Age) + \beta_{22}(Arrests) + \beta_{23}(Race) + \beta_{24}(Ethnicity) +$$
$$\beta_{25}(Risk) + \beta_{26}(Controls) + \beta_{27}(Discontinued) + r_{2i}$$

The Level-1 model above is the same as in previous equations. In the Level-2 model, the intercept μ_{0i} for participant *i* is equal to the intercept β_{00} (mean number of days incarcerated across all participants), plus the effect of age (β_{01}), plus the effect of number of prior arrests (β_{02}), plus the effect of race (β_{03}), plus the effect of ethnicity (β_{04}), plus the effect of risk classification (β_{05}), plus the group effect (β_{06} and β_{07}), plus the between-person residuals on days incarcerated (r_{0i}). The slope of the linear term at Level-1 (μ_{1i}) is equal to the intercept β_{10} (mean slope of linear change in days incarcerated across all participants), plus the slopes of the static factors (β_{11} to β_{17}), plus the between-person residuals on days incarcerated (r_{1i}). Similarly, the slope of the quadratic term at Level-1 (μ_{2i}) is equal to the intercept β_{20} (mean slope of quadratic change in days incarcerated across all participants), plus the slopes of the static factors (β_{21} to β_{27}), plus the between-person residuals on days incarcerated (r_{2i}).

The results revealed that the intercept was significantly different from zero (see Model 4 in Table 8): β_{00} = 33.48, *SE* = 14.40, *t*(383) = 2.33, *p* = .021. In other words, the average number of days incarcerated in Year 1 was 33 days, while controlling for everything else in the model. The main effects of age, arrests, race, and ethnicity were not significant: β_{01} = -0.44, *SE* = 0.77, *t*(383) = -0.58, *p* = .565; β_{02} = 2.24, *SE* = 1.45, *t*(383) = 1.54, *p* = .124; β_{03} = 9.97, *SE* = 12.60, *t*(383) = 0.79, *p* = .429; β_{04} = 6.49, *SE* = 14.69, *t*(383) = 0.44, *p* = .659. On the other hand, risk scores and group were significantly associated with days incarcerated: β_{05} = 32.63, *SE* = 13.38, *t*(383) = 2.44, *p* = .015; β_{06} = 41.17, *SE* = 13.76, *t*(383) = 2.99, *p* = .003; β_{07} = 58.45, *SE* = 13.48, *t*(383) = 4.34, *p* < .001. Individuals classified as high risk on average spent 33 more days incarcerated in Year 1 post-release compared to those classified as low risk, while controlling for other variables in the model. Compared to people who completed the aftercare program, those in the control group spent an additional 41 days incarcerated in Year 1, and those who did not completed the aftercare program spent an additional 58 days incarcerated in Year 1. When the analysis was re-run to compare people in the control group to people who discontinued aftercare, the results revealed the two groups were not significantly different from each other, β_{08} = 17.28, *SE* = 15.38, *t*(383) = 1.12, *p* = .262.

Table 8

Models 4-7: Level-2 Static Factors

Fixed Effect	Model 4		Model 5		Model 6		Model 7	
	π	*SE*	π	*SE*	π	*SE*	π	*SE*
Intercept, β_{00}	33.48	14.40	28.81	13.98	34.36	11.61	34.80	10.69
Age, β_{01}	-0.44*	0.77	-0.52*	0.74	-0.94	0.57	-0.94	0.57
Arrests, β_{02}	2.24*	1.45	2.50	1.41	2.73	1.15	2.74	1.15
Black, β_{03}	9.97*	12.60	12.97*	12.53	17.03	8.89	16.62	7.66
Hispanic, β_{04}	6.49*	14.69	13.83*	14.24	1.07*	10.35		
High Risk, β_{05}	32.63	13.38	34.81	12.20	28.61	8.85	28.56	8.89
Controls, β_{06}	41.17	13.76	42.14	13.69	40.38	13.58	40.34	13.58
Discontinued, β_{07}	58.45	13.48	58.24	13.51	59.08	13.51	59.12	13.55
Linear Slope, β_{10}	5.71	3.06	8.24	2.15	8.79	1.87	8.79	1.87
Age, β_{11}	-0.09*	0.16	-0.05*	0.06				
Arrests, β_{12}	0.17*	0.30	0.03*	0.11				
Black, β_{13}	4.44	2.37	2.81*	2.27				

Table 8 (continued)

Fixed Effect	Model 4		Model 5		Model 6		Model 7	
	π	*SE*	π	*SE*	π	*SE*	π	*SE*
Hispanic, β_{14}	2.53*	2.90	-1.41*	1.04				
High Risk, β_{15}	0.49*	2.62	-0.70*	0.92				
Controls, β_{16}	-8.87	2.87	-9.39	2.75	-9.31	2.74	-9.31	2.74
Discontinued, β_{17}	-7.81	2.55	-7.70	2.57	-7.97	2.59	-7.97	2.59
Quadratic Slope, β_{20}	-0.27	0.12	-0.38	0.08	-0.44	0.07	-0.44	0.07
Age, β_{21}	0.00*	0.01						
Arrests, β_{22}	-0.01*	0.01						
Black, β_{23}	-0.20	0.09	-0.13*	0.09				
Hispanic, β_{24}	-0.17*	0.12						
High Risk, β_{25}	-0.05*	0.10						
Controls, β_{26}	0.34	0.11	0.36	0.11	0.37	0.11	0.37	0.11
Discontinued, β_{27}	-.27	0.10	0.27	0.11	0.28	0.11	0.28	0.11
Random Effect	Estimate		Estimate		Estimate		Estimate	
Within-person, e_{ti}	10,064.54		10,064.83		10,065.19		10,065.25	
Intercept, r_{0i}	8,890.35		8,906.34		8,927.96		8,928.66	
Linear Slope, r_{1i}	328.96		332.14		334.30		334.25	
Quadratic Slope, r_{2i}	0.50		0.51		0.51		0.51	
Deviance (parameters)	108,946.25 (31)		108,948.88 (27)		108,954.16 (21)		108,954.16 (20)	

Note. SE = standard error.

* Coefficient is not significant, *p* > .10; All other values are significant (p ≤ .10).

Model 4 = Equation 3
Model 5 = Non-significant quadratic slope predictors removed
Model 6 = Non-significant linear slope predictors removed
Model 7 = Non-significant intercept predictors removed

In the full static factor model (Model 4), the linear slope was significant, β_{10} = 5.71, *SE* = 3.06, *t*(383) = 1.87, *p* = .062. Race and group were the only significant predictors of the linear slope: β_{13} = 4.44, *SE* = 2.37, *t*(383) = 1.88, *p* = .061; β_{16} = -8.87, *SE* = 2.87, *t*(383) = -3.09, *p* = .002; β_{17} = -7.81, *SE* = 2.55, *t*(383) = -3.07, *p* = .002. The significant cross-level interactions suggest the rate of linear change in days incarcerated differs with regard to race and group. The control group was not significantly different from the group that did not complete the aftercare program, β_{18} = 1.07, *SE* = 2.80, *t*(383) = 0.38, *p* = .703. There were no significant impacts of age, arrests, ethnicity, or risk on the linear slope of time (all *p*s > .383; see Model 4 in Table 8). The quadratic slope was also significant: β_{20} = -0.27, *SE* = 0.12, *t*(383) = -2.19 *p* = .029. Race and group were the only predictors significantly associated with the quadratic slope of time at Level-1. The rate of acceleration was different among White and Black participants, β_{23} = -0.20, *SE* = 0.09, *t*(383) = -2.10, *p* = .036. The rate of acceleration was also different among those who completed the aftercare program compared to controls, β_{26} = 0.34, *SE* = 0.11, *t*(383) = 3.01, *p* = .003, and compared to those who discontinued the aftercare program, β_{27} = 0.27, *SE* = 0.10, *t*(383) = 2.63, *p* = .009. The control group was not significantly different from the group that did not complete the aftercare program, β_{28} = -0.06, *SE* = 0.11, *t*(383) = -0.56, *p* = .573. Note that when non-significant predictors of the quadratic slope were removed (Model 5), race was no longer significant (β_{23} = -0.13, *SE* = 0.09, *t*(387) = -1.41, *p* = .158), and thus was removed from future model iterations. After removing non-significant predictors of the quadratic slope (see Model 5 in Table 8), non-significant predictors were removed from the linear slope analyses (see Model 6 in Table 8), and then from the intercept, such that the final static model consisted of only significant static factors (see Model 7 in Table 8).

Model 7 included only significant static predictors of the intercept, linear slope, and quadratic slope. The intercept was significantly different from zero when everything else in the model was equal to zero, β_{00} = 34.80, *SE* = 10.69, *t*(384) = 3.25, *p* < .001. In other words, the average number of days incarcerated was 35 days in the first-year post-release, among clients who were White, low risk, completed the aftercare program, and with age (*M* = 34.47) and number of prior arrests (*M* = 7.73) equal to the grand mean. The main effect of age was significant while controlling for everything else in the model, β_{01} = -0.94, *SE* = 0.57, *t*(384) = -1.67, *p* = .096, suggesting each additional unit increase in age was associated with one less day incarcerated in Year 1. The main effects of number of prior arrests was also significant while controlling for everything else in the model, β_{02} = 2.74, *SE* = 1.15, *t*(384) = 2.38, *p* = .018, suggesting each additional prior arrest was associated with three additional days incarcerated in Year 1. The main effect of race was significant, β_{03} = 16.62, *SE* = 7.66, *t*(384) = 2.17, *p* = .031, suggesting that, while controlling for everything else in the model, Black participants spent 17 more days incarcerated Year 1 when compared to White participants. There was a significant main effect of risk classification, β_{05} = 28.56, *SE* = 8.89, *t*(384) = 3.22, *p* = .001, indicating that high-risk participants spent an additional 29 days incarcerated in Year 1 compared to low-risk participants. Finally, there was a significant main effect of group. Participants in the control group spent about 40 more days incarcerated in Year 1 compared to participants who completed the aftercare program, β_{06} = 40.34, *SE* = 13.58, *t*(384) = 2.97, *p* = .003, and participants who discontinued aftercare spent approximately 59 more days incarcerated in Year 1 compared to those who completed aftercare, β_{07} = 59.12, *SE* = 13.55, *t*(384) = 4.36, *p* < .001. When the analysis was re-run with controls serving as the reference group, the results indicated a non-significant difference between the control group and aftercare non-completers, β_{08} = 18.78, *SE* = 15.20, *t*(384) = 1.24, *p* = .218.

In Model 7, both the linear and quadratic slopes were significant, β_{10} = 8.79, *SE* = 1.87, *t*(388) = 4.71, *p* < .001; β_{20} = -0.44, *SE* = 0.07, *t*(388) = -5.93, *p* < .001. Group was the only remaining significant predictor of the linear and quadratic slopes. In predicting the linear slope, aftercare completers were significantly different from the control group, β_{16} = -9.31, *SE* = 2.74, *t*(388) = -3.40, $p < .001$, and from the aftercare discontinued group, β_{17} = -7.97, *SE* = 2.59, *t*(388) = -3.08, $p = .002$. The control group was not significantly different from those who did not complete the aftercare program, β_{18} = 1.34, *SE* = 2.69, *t*(388) = .50, $p = .619$. In predicting the quadratic slope, the same pattern of results emerged. Specifically, aftercare completers were significantly different from controls, β_{26} = 0.37, *SE* = 0.11, *t*(388) = 3.44, $p < .001$, and from non-completers, β_{27} = 0.28, *SE* = 0.11, *t*(388) = 2.64, $p = .009$. The control group was not significantly different from the group that discontinued the aftercare program, β_{28} = -0.09, *SE* = 0.11, *t*(388) = -0.81, $p = .418$. Significant cross-level interactions are unpacked in the final model (Model 11).

The deviance test indicated that the 2-level static factor model with all static predictors at Level-2 (Model 4) fit the data better than the previous model that included linear and quadratic terms at Level-1 (Model 3), $\chi^2(21) = 62.70$, $p < .001$. The final static model (with only significant predictors; Model 7) was also compared to the previous model that included linear and quadratic terms at Level-1 (Model 3), and it showed a significant improvement in model fit, $\chi^2(10) = 54.79$, $p < .001$. Results indicate that Model 7 explained 10% of the variance in the intercept, 5% of the variance in the linear slope, and 6% of the variance in the quadratic slope.

Criminogenic Needs

In the full model, the variables number of family members regularly stayed in contact with (grand mean centered), amount of money per week earned illegally (grand mean centered), risk-taking (grand mean centered), alcohol dependence (dummy-coded: 0 = No, 1 = Yes), and friends engaged in illegal activities (grand mean centered) were added at Level-2 to test their impact on the initial level and the rate of linear and quadratic change in days incarcerated. The general full model equation is as follows (Equation 4):

$$
\begin{aligned}
Days\ Incarcerated_{ti} &= \pi_{0i} + \pi_{1i}(Linear_{1i}) + \pi_{2i}(Quadratic_{ti}) + e_{ti} \\
\mu_{0i} &= \beta_{00} + \beta_{01}(Age) + \beta_{02}(Arrests) + \beta_{03}(Race) + \beta_{04}(Risk) + \\
&\quad \beta_{05}(Controls) + \beta_{06}(Discontinued) + \beta_{07}(Family) + \\
&\quad \beta_{08}(Illegal\ Earnings) + \beta_{09}(Risk\ Taking) + \\
&\quad \beta_{010}(Alcohol\ Dependence) + \beta_{011}(Procriminal\ Friends) + r_{0i} \qquad (4) \\
\mu_{1i} &= \beta_{10} + \beta_{11}(Controls) + \beta_{12}(Discontinued) + \beta_{13}(Family) + \\
&\quad \beta_{14}(Illegal\ Earnings) + \beta_{15}(Risk\ Taking) + \\
&\quad \beta_{16}(Alcohol\ Dependence) + \beta_{17}(Procriminal\ Friends) + r_{1i} \\
\mu_{2i} &= \beta_{20} + \beta_{21}(Controls) + \beta_{22}(Discontinued) + \beta_{23}(Family) + \\
&\quad \beta_{24}(Illegal\ Earnings) + \beta_{25}(Risk\ Taking) + \\
&\quad \beta_{26}(Alcohol\ Dependence) + \beta_{27}(Procriminal\ Friends) + r_{2i}
\end{aligned}
$$

Again, the Level-1 model equation is unchanged from equations. In the Level-2 model, the intercept μ_{0i} for participant *i* is equal to the intercept β_{00} (mean number of days incarcerated across all participants), plus the effect of age (β_{01}), plus the effect of number of prior arrests (β_{02}), plus the effect of race (β_{03}), plus the effect of risk (β_{04}), plus the effect of group (β_{05} and β_{06}), plus the effect of number of close family members (β_{07}), plus the effect of amount of money per week made illegally (β_{08}), plus the effect of risk-taking (β_{09}), plus the effect of alcohol dependence (β_{010}), plus the effect of pro-criminal friends (β_{011}), plus the between-person residuals on days incarcerated (r_{0i}). The slope of the linear term at Level-1 (μ_{1i}) is equal to the intercept β_{10} (mean slope of linear change in days incarcerated across all participants), plus the group effect (β_{11} and β_{12}), plus the effects of the dynamic factors (β_{13} to β_{17}), plus the between-person residuals on days incarcerated (r_{1i}). Similarly, the slope of the quadratic term at Level-1 (μ_{2i}) is equal to the intercept β_{20} (mean slope of quadratic change in days incarcerated across all participants), plus the group effect (β_{21} and β_{22}), plus the effects of the dynamic factors (β_{23} to β_{27}), plus the between-person residuals on days incarcerated (r_{2i}).

The main effects of age, arrests, race, risk, group, and close family members were not significant (*p*s > .120; see Model 8 in Table 9). Illegal earnings was positively associated with days incarcerated, β_{08} = 0.01, *SE* = 0.003, *t*(80) = 3.66, *p* < .001. The effect of risk-taking was also significant, β_{09} = 11.04, *SE* = 6.40, *t*(80) = 1.73, *p* = .088. Alcohol dependence was also related to a higher number of days incarcerated in the year following initial release from prison, β_{010} = 57.54, *SE* = 20.72, *t*(80) = 2.78, *p* = .007. Lastly, the effect of pro-criminal friends was significant, β_{011} = -16.24, *SE* = 7.58, *t*(80) = -2.14, *p* = .035.

Table 9

Models 8-10: Level-2 Criminogenic Needs

Fixed Effect	Model 8		Model 9		Model 10	
	π	*SE*	π	SE	π	*SE*
Intercept, β_{00}	22.67*	29.98	32.35*	29.64	42.30*	28.86
Age, β_{01}	-1.48*	1.35	-1.56*	1.36	-1.56*	1.37
Arrests, β_{02}	3.24*	2.07	3.32*	2.06	3.34*	2.06
Black, β_{03}	18.47*	17.94	18.81*	17.90	19.72*	18.01
High Risk, β_{04}	20.45*	18.07	20.20*	18.08	21.09*	18.09
Controls, β_{05}	7.61*	32.95	-1.13*	34.64	-16.03*	26.17
Discontinued, β_{06}	36.90*	23.45	27.48*	22.12	11.35*	18.31
Family, β_{07}	-1.98*	1.70	-1.88*	1.67	-2.03*	1.67
Illegal Earnings, β_{08}	0.01	0.00	0.01	0.00	0.01	0.00
Risk-Taking, β_{09}	11.04	6.40	8.95*	6.20	10.65	5.41

Table 9 (continued)

Fixed Effect	Model 8		Model 9		Model 10	
	π	*SE*	π	SE	π	*SE*
Alcohol Dependence, β_{010}	57.54	20.72	59.21	19.58	47.48	15.38
Pro-criminal Friends, β_{011}	-16.24	7.58	15.08	7.21	-15.30	7.13
Linear Slope, β_{10}	10.56*	6.48	3.83*	3.09	2.15	2.69
Controls, β_{11}	-8.82*	8.88	-2.44*	2.20		
Discontinued, β_{12}	-9.18	5.25	-2.30*	1.65		
Family, β_{13}	0.50*	0.46	0.43	0.15	0.46	0.16
Illegal Earnings, β_{14}	-0.00*	0.00	-0.00*	0.00		
Risk-Taking, β_{15}	-1.23*	1.66	0.26*	0.51		
Alcohol Dependence, β_{16}	-0.45*	5.21	-1.76*	1.53		
Pro-criminal Friends, β_{17}	2.11*	1.81	1.22	0.53	1.27	0.51
Quadratic Slope, β_{20}	-0.63	0.27	-0.34	0.10	-0.34	0.10
Controls, β_{21}	0.28*	0.41				
Discontinued, β_{22}	0.30*	0.22				
Family, β_{23}	-0.00*	0.02				
Illegal Earnings, β_{24}	0.00*	0.00				
Risk-Taking, β_{25}	0.07*	0.07				
Alcohol Dependence, β_{26}	-0.06*	0.22				
Pro-criminal Friends, β_{27}	-0.04*	0.08				
Random Effect	Estimate		Estimate		Estimate	
Within-person, e_{ti}	9,421.14		9,418.85		9,418.02	
Intercept, r_{0i}	6,068.87		6,114.95		6,355.54	
Linear Slope, r_{1i}	414.56		443.23		457.34	
Quadratic Slope, r_{2i}	0.71		0.77		0.77	
Deviance (parameters)	25,870.51 (35)		25,875.63 (28)		25,880.60 (23)	

Note. SE = standard error.

* Coefficient is not significant, $p > .10$; All other values are significant, $p \leq .10$.

Model 8 = Equation 4

Model 9 = Non-significant quadratic slope predictors removed
Model 10 = Non-significant linear slope predictors removed

Although the linear slope was not significant in Model 8, β_{10} = 10.56, *SE* = 6.48, *t*(84) = 1.63, *p* = .107, there was a significant difference in the linear trend of aftercare completers and non-completers, β_{12} = -9.18, *SE* = 5.25, *t*(84) = -1.75, *p* < .084. No other predictors were significantly associated with the linear slope (*p*s > .248). The quadratic slope was significant and decelerating, β_{20} = -0.63, *SE* = 0.27, *t*(84) = -2.33, *p* = .022, but the quadratic slope was not related to any of the predictors (*p*s > .165). The deviance test indicated that the full dynamic needs model (Model 8) fit the data better than the static factor model (Model 7), $\chi^2(15)$ = 83,083.65, *p* < .001.

After removing non-significant predictors of the quadratic slope, both family and pro-criminal friends were significantly related to the linear slope (see Model 9 in Table 9): β_{13} = 0.43, *SE* = 0.15, *t*(84) = 2.79, *p* = .007; β_{17} = 1.22, *SE* = 0.53, *t*(84) = 2.29, *p* = .025, respectively. There were no other significant predictors of the linear slope in Model 9 (*p*s > .168). The cross-level interactions between the linear trend and family and pro-criminal friends remained significant when other non-significant linear predictors were removed from the model (see Model 10 in Table 9): β_{13} = 0.46, *SE* = 0.16, *t*(89) = 2.90, *p* = .005; β_{17} = 1.27, *SE* = 0.51, *t*(89) = 2.50, *p* = .014. However, the linear trend remained non-significant, β_{10} = 2.15, *SE* = 2.69, *t*(89) = 0.80, *p* = .426. The significant cross-level interactions are unpacked in the final model (Model 11).

The Final Model

Non-significant predictors were removed from one Level-1 variable at a time, starting with the quadratic term, followed by the linear term, and then finally the intercept. This is based on the suggestion from Anderson (2012) in which he recommends removing non-significant variables from the highest order term (i.e., quadratic term) first, and then re-running the model with all variables included in the second highest order term (i.e., linear term) because after eliminating variables in the quadratic term, it is possible for variables in the linear term to become significant. In the final HLM model, family, illegal earnings, risk-taking, alcohol dependence, and pro-criminal friends were retained at Level-2, and the linear and quadratic terms were retained at Level-1. The final model equation (Equation 5) was as follows:

$$\begin{aligned} Days\ Incarcerated_{ti} &= \pi_{0i} + \pi_{1i}(Linear_{1i}) + \pi_{2i}(Quadratic_{ti}) + e_{ti} \\ \mu_{0i} &= \beta_{00} + \beta_{01}(Family) + \beta_{02}(Illegal\ Earnings) + \beta_{03}(Risk\ Taking) + \\ &\quad \beta_{04}(Alcohol\ Dependence) + \beta_{05}(Procriminal\ Friends) + r_{0i} \qquad (5) \\ \mu_{1i} &= \beta_{10} + \beta_{11}(Family) + \beta_{12}(Procriminal\ Friends) + r_{1i} \\ \mu_{2i} &= \beta_{20} + r_{2i} \end{aligned}$$

In the Level-1 model above, days incarcerated for participant *i* at time *t* is equal to the intercept π_{0i} (mean days incarcerated at Year 1), plus the effects of slope π_{1i} (linear change in days incarcerated from one year to the next) and slope π_{2i} (quadratic change in days incarcerated from one year to the next), plus the residual error between predicted and observed scores at each observation time, e_{ti}. In the Level-2 model, the intercept μ_{0i} for participant *i* is equal to the intercept β_{00} (mean number of days incarcerated across all participants), plus the effect of the number of close family members (β_{01}), plus the effect of amount of money earned illegally per week (β_{02}), plus the effect of risk-taking (β_{03}), plus the effect of alcohol dependence (β_{04}), plus the effect of pro-criminal friends (β_{05}), plus the between-person residuals on days incarcerated (r_{0i}). The slope of the linear term at Level-1 (μ_{1i}) is equal to the intercept β_{10} (mean slope of linear change in days incarcerated across all participants), plus the effect of number of close family members (β_{11}), plus the effect of pro-criminal friends (β_{12}), plus the between-individual residuals on days incarcerated (r_{1i}). The slope of the quadratic term at Level-1 (μ_{2i}) is equal to the intercept β_{20} (mean slope of quadratic change in days incarcerated across all the participants), plus the between-person residuals on days incarcerated (r_{2i}).

Final model (Model 11) results are presented in Table 10. The intercept was significantly different from zero when everything else in the model was equal to zero, β_{00} = 62.34, *SE* = 21.19, *t*(86) = 2.94, *p* = .004. In other words, the average number of days incarcerated was 62 days in the first year following initial discharge, among clients without alcohol dependence, and with family relationships (*M* = 6.38), illegal earnings (*M* = $1,578.05), risk-taking scores (*M* = 4.18), and pro-criminal friends (*M* = 1.85) equal to the grand means. The main effect of illegal earnings was significant while controlling for everything else in the model, β_{02} = 0.01, *SE* < 0.00, *t*(86) = 2.26, *p* = .027, suggesting higher illegal earnings were related to more days incarcerated. The main effect of risk-taking was also significant, β_{03} = 9.13, *SE* = 4.70, *t*(86) = 1.94, *p* = .055. Each unit increase in risk-taking was associated with an additional 9 days incarcerated in the first-year post-release, while controlling for all other variables in the model. Alcohol dependence was associated with more days incarcerated in the first year post-release, β_{04} = 53.81, *SE* = 16.84, *t*(86) = 3.20, *p* = .002. Specifically, clients with alcohol dependence spent on average 54 more days incarcerated in the first year than individuals without alcohol dependence. Finally, there was a main effect of pro-criminal friends, β_{05} = -11.86, *SE* = 7.00, *t*(86) = -1.69, *p* = .094. Although the main effect of family was not significant, it was included as an intercept predictor so that simple slope analyses could be performed on the significant cross-level interaction: β_{01} = -1.34, *SE* = 1.74, *t*(86) = -0.77, *p* = .444.

Table 10

Model 11: Final Model

Fixed Effect	$\pi(SE)$	*t*	*df*	*p*
Intercept, β_{00}	62.34(21.19)	2.94	86	.004
Family, β_{01}	-1.34(1.74)	-0.77	86	.444
Illegal Earnings, β_{02}	0.01(0.00)	2.26	86	.027
Risk-Taking, β_{03}	9.13(4.70)	1.94	86	.055
Alcohol Dependence, β_{04}	53.81(16.84)	3.20	86	.002
Pro-criminal Friends, β_{05}	-11.86(7.00)	-1.69	86	.094
Linear Slope, β_{10}	2.14(2.68)	0.80	89	.426
Family, β_{11}	0.45(0.16)	2.81	89	.006
Pro-criminal Friends, β_{12}	1.28(0.51)	2.53	89	.013
Quadratic Slope, β_{20}	-0.34(0.10)	-3.23	91	.002
Random Effect	Estimate			
Within-person, e_{ti}	9,416.45			
Intercept, r_{0i}	6,819.82			
Linear Slope, r_{1i}	457.36			
Quadratic Slope, r_{2i}	0.77			
Deviance (parameters)	25,888.80 (17)			

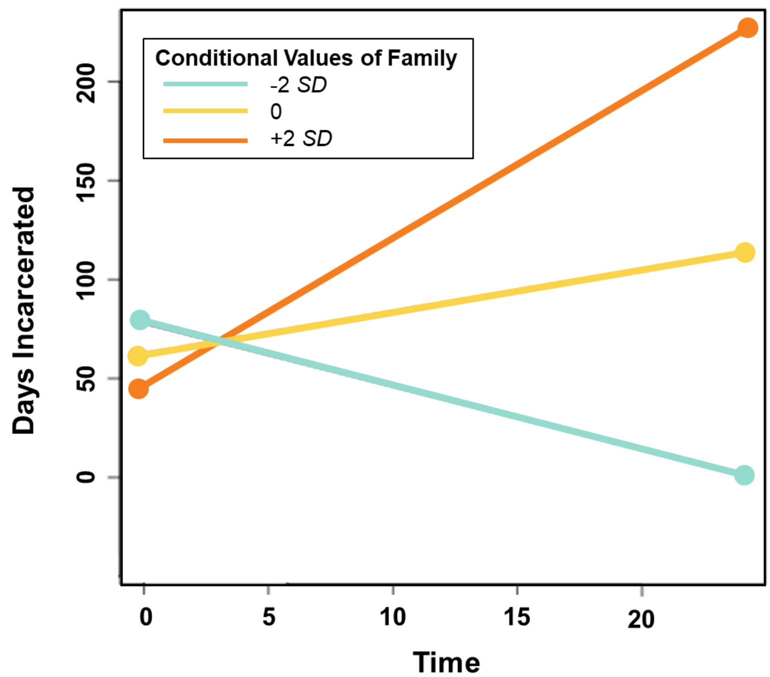
Note. SE = standard error.

The results showed that days incarcerated increased over time: each year post-release, the number of days incarcerated increased 2.14 days, although the linear trend was not significant. This is potentially due to issues with multicollinearity between the linear trend, the main effects of family and pro-criminal friends, plus the two cross-level interactions. Nevertheless, both the linear trend and main effects of family and pro-criminal friends were retained in the final model so that simple slope analyses could be conducted on the cross-level interactions: Specifically, the significant effects of family and pro-criminal friends on the linear slope of days incarcerated: β_{11}

= 0.45, *SE* = 0.16, *t*(89) = 2.81, *p* = .006; β_{12} = 1.28, *SE* = 0.51, *t*(89) = 2.53, *p* = .013, respectively. The quadratic term was negative, indicating concave growth. For each additional year post-release, the rate of acceleration decreased 0.34 days.

Figure 5

Simple Slope Analyses: Family x Linear Trend

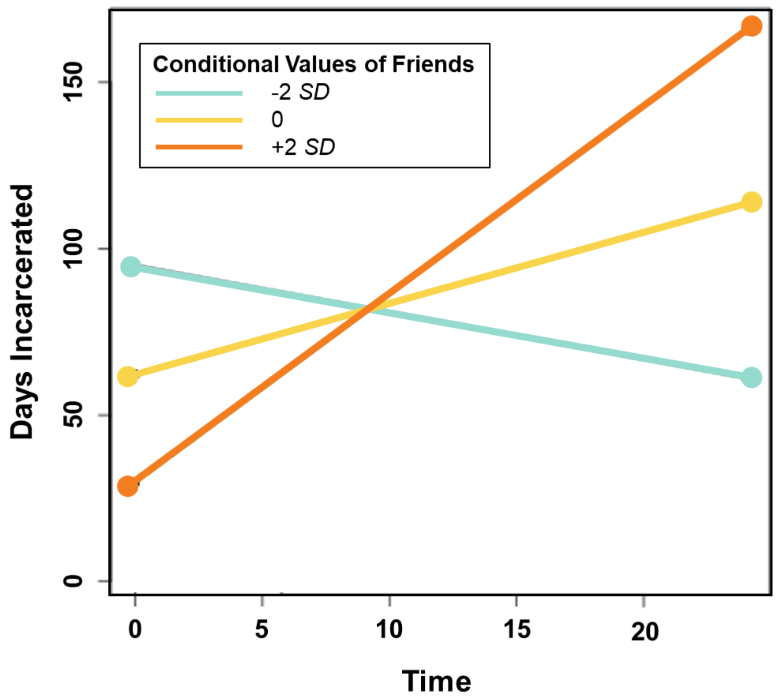


Note. The simple slope of Family +2 *SD* is significant (*p* = .010). The other simple slopes were not significant (*p*s > .369). *SD* = standard deviation.

Further analyses and the simple slope tests were conducted with the established procedures (Preacher et al., 2006). First, simple slope analyses were conducted to unpack the significant 2-way interaction between family and the linear slope (see Figure 5). Conditional values were evaluated at the mean ± 2 *SD* of the number of close family members (*M* = 6.38, *SD* = 5.97). The relationship between the linear trend and the number of days incarcerated was positive at high (*b* = 7.46, *SE* = 2.80, *t* = 2.66, *p* = .009) numbers of close family members, which contradicts theoretical expectations. At low (*b* = -3.17, *SE* = 3.50, *t* = -0.91, *p* = .367) and average (b = 2.14, SE = 2.76, t = 0.78, p = .439) numbers of close family members, this relationship was not significant.

Figure 6

Simple Slope Analyses: Pro-criminal Friends x Linear Trend



Note. The simple slope of Pro-criminal Friends +2 *SD* is significant (p = .042). The other simple slopes were not significant (*ps* > .445). *SD* = standard deviation.

Simple slope analyses were again conducted to unpack the significant 2-way interaction between pro-criminal friends and the linear slope (see Figure 6). Conditional values were evaluated at the mean ±2 *SD* of pro-criminal friends (M = 1.85, SD = 1.38). The relationship between the linear trend and days incarcerated positive at high levels of pro-criminal friends, b = 5.68, SE = 2.73, t = 2.08, p = .040. This relationship was not significant at low (b = -1.39, SE = 3.60, t = -0.39, p = .700) or average (b = 2.14, SE = 2.76, t = 0.78, p = .439) levels of pro-criminal friends.

The deviance test indicated the final model (Model 11) fit the data better than the static factor model (Model 7), $\chi^2(3) = 83{,}065.37$, $p < .001$. The variance components indicated that there was variation in days incarcerated, the linear slope between individuals, and the quadratic slope: $Var = 6819.82$, $df = 84$, $\chi^2 = 300.44$, $p < .001$; $Var = 457.36$, $df = 87$, $\chi^2 = 477.16$, $p < .001$; $Var = 0.77$, $df = 89$, $\chi^2 = 476.82$, $p < .001$, respectively. Compared to the empty model, number of close family members, illegal earnings, risk-taking, alcohol dependence, and pro-criminal friends explained 5.81% variance between individuals, and family and friend measures explained 32.30% of the variance in the linear slope. Results indicate that the final model explained 31% of the variance in the intercept. Since the variance in the linear and quadratic slope increased relative to the unconditional growth model, effect sizes could not be calculated.

Section IV: Discussion

The prevalence of mass incarceration, coupled with the concurrent increase in substance use disorders and overdoses following the COVID-19 pandemic (e.g., Ahmad et al., 2021; Jalal et al., 2018; Niles et al., 2021; Volkow & Blanco, 2021), poses a major public health concern for policymakers in the United States. Given the significant overlap between justice-involved and substance-using populations, the justice system is uniquely positioned to address criminogenic and behavioral health needs for this at-risk population. Put another way, correctional rehabilitation programs have the opportunity to provide this population the necessary treatment services to help people successfully transition back into the community following a period of incarceration. Moreover, the current cultural focus on CJ policies and procedures warrants an assessment of historical trends in recidivism rates to better understand needed programmatic changes that potentially could lead to improved client outcomes.

The RNR model is perhaps the most widely used framework for providing justice-involved populations individualized treatment. In brief, this model prescribes that clients' individual risks and criminogenic needs be accounted for at treatment intake as a way to inform treatment programs of an individual's potential future involvement with the justice system and associated clinical needs that should be addressed during treatment. Risks for recidivism include static factors, such as age, criminal history, and assigned sex at birth, that cannot be changed through treatment. Criminogenic needs include potentially changeable clinical targets that can be influenced and targeted by the program as a means of reducing criminal behavior.

Studies evaluating the effectiveness of empirically based treatment have commonly used follow-up periods of 2 years or less (Andersen & Skardhamar, 2017; e.g., Armstrong & McNeill, 2012; Farrington & Davies, 2007; Graunbøl et al., 2010). Although these studies provide evidence for the short-term effectiveness of treatment, they are limited in that they do not give insight into the long-term effects of services intended to reduce criminal behavior across the lifespan. For this reason, the present study evaluated the effects of treatment and aftercare among clients that were released from prison across a 25-year time period. Notably, findings from the present study demonstrate that the asymptote of rearrest and reincarceration trajectories does not occur until 10-15 years post-release. Whereas Alper et al. (2018) reported that 60% of rearrests occurred after the third year of a 9-year follow-up, this study found that 37% of rearrests by the fifteenth year (n = 323) occurred after Year 3 (n = 205). Thirty-one percent of reincarcerations at Year 15 (n = 318) occurred after Year 3 (n = 218). Furthermore, the plateau period appears to occur earlier for individuals classified as high risk (Year 10) than for people who are low risk (Year 15). Investigations with longer follow-up periods are capable of providing valuable information about fluctuations in recidivism and desistance across time that can be used to inform community-based programs that support clients long after their release.

The current study was a longitudinal examination of rearrest and reincarceration across 25 years. A series of Kaplan-Meier survival regressions showed that treatment receipt was not related to time to rearrest (**H1a**). Follow-up analyses revealed that high-risk people in both the treatment and control groups were more likely to be rearrested than low-risk people in the control group. These findings are partially consistent with predictions based on the RNR model, which dictate the need to align treatment intensity with a person's risk of recidivism (based on their static risk factors and criminogenic needs; Bonta & Andrews, 2007). It was hypothesized that, among high-risk participants, treatment receipt would be associated with a longer time to rearrest when compared to no treatment; among low-risk participants, treatment receipt was expected to be associated with a shorter time to rearrest when compared to no treatment (**H1b**). Providing intensive treatment to high-risk people should therefore have resulted in significantly lower hazard rates for rearrest than high-risk participants who did not receive treatment. This was not observed in the present study: high-risk individuals from the treatment program were not different from high-risk individuals from the control group. Correspondingly, the misalignment between treatment intensity and need for low-risk participants would have forecast a greater hazard rate for this group than low-risk participants who did not receive treatment. However, this difference was also not significant. Rather, low-risk controls were significantly less likely to be rearrested than high-risk individuals (in both the treatment and control groups). Collectively, (1) the non-significant difference between low-risk people in the treatment group and high-risk people regardless of treatment receipt, and (2) the significantly lower hazard rate for low-risk participants in the control group compared to high-risk participants regardless of treatment receipt, suggests the treatment program may have negatively impacted low-risk participants. This is consistent with previous literature reporting a potentially iatrogenic impact of putting low-risk individuals into intensive treatment programs. For example, Bonta et al. (2000) reported a 15% recidivism rate when clients categorized as low risk for reoffending received minimal treatment; in contrast, low-risk clients who received intensive treatment had more than double the recidivism rate (32%). Similarly, Evans et al. (2011) found similar rearrest rates among high-risk individuals with shorter treatment lengths and low-risk individuals with longer treatment lengths, both of which had higher rearrest rates than their high-risk counterparts with longer treatment lengths and low-risk counterparts with shorter treatment lengths.

The lack of positive treatment effect was further explored in a series of follow-up analyses assessing the effect of aftercare completion. As hypothesized, aftercare completion extended the amount of time to rearrest when compared to people who did not complete aftercare (**H2a**). Cox regressions showed that high-risk people who did not complete the aftercare program were significantly more likely to be rearrested than individuals who completed the aftercare program, even while controlling for risk level (**H2b**). In line with hypotheses, high-risk aftercare completers were not different from low-risk participants regardless of aftercare completion (**H2b**). These results highlight the importance of aftercare completion, especially for people at a high risk of recidivism. Low-risk aftercare non-completers had a shorter median time to rearrest than those who completed the aftercare program (again regardless of risk level), although these differences were not significant. Together, the results underscore the importance of reserving intensive treatment programs for those who are most at-risk of recidivating, as well as the importance of aftercare completion.

Indeed, providing intensive services to low-risk individuals may actually increase their risk of future recidivism (Bonta et al., 2000). Notably, aftercare completion appears to be effective at reducing recidivism rates among both high- and low-risk individuals. For this reason, justice agencies should implement motivational strategies and policies designed to promote aftercare completion. Importantly, previous studies have distinguished between mandatory and voluntary aftercare in terms of their effectiveness at reducing recidivism rates; that is, mandatory aftercare was not effective, whereas voluntary programs were effective (Galassi et al., 2015; Welsh et al., 2014). Therefore, agency strategies should consider incentivizing aftercare completion while refraining from explicitly mandating it. For example, clients may be encouraged to complete aftercare by offering reductions in community supervision terms, reducing meeting frequency with supervising officers, or perhaps by creating programs designed to assist aftercare completers in procuring employment, better housing options, or some other form of special assistance.

To fully utilize the 25-year follow-up period, a longitudinal growth model assessed the effects of static and dynamic factors on the number of days incarcerated per year. Results showed that static factors (number of prior arrests, race, risk classification, and aftercare completion) were prospectively associated with the number of days incarcerated across the 25-year time period. Next, proxy measures of the criminogenic needs (i.e., poor family relationships, pro-criminal attitudes, antisocial personality pattern, substance use, and social supports for crime) were evaluated within the multilevel framework to determine whether these factors added in the prediction of days incarcerated, above and beyond risk assessments alone. In the final model, number of close family members, illegal earnings, risk-taking, alcohol dependence, and pro-criminal friends emerged as significant predictors of the amount of time incarcerated over 25 years, even while controlling for risk factors in the model. Importantly, static factors were no longer significant after entering criminogenic needs into the model. This deviates from existing literature that presents static factors as most consistently associated with recidivism (Coid et al., 2016; Hannah-Moffat, 2013; Proulx et al., 1997; Skeem, 2013; Van Voorhis & Presser, 2001; Van Voorhis et al., 2010). For example, in a 36-month follow-up study of 24,972 justice-involved people, Caudy et al. (2013) reported that static factors were better at predicting recidivism than dynamic factors. The contradiction between past literature and present findings may be related to the extended follow-up period. Specifically, static factors may predict short-term recidivism, while dynamic factors may be more appropriate for predicting long-term recidivism. Implications are discussed in detail at the end of this section.

As predicted, affiliation with peers engaged in illegal activities emerged as a predictor of rising reincarceration rates over the lifespan. Contrary to expectations, close relationships with many family members were associated with increasing rates of reincarceration over time. It is worth noting, however, that the measure of family relationships utilized in the present study only assesses the number of close family relationships, and therefore may not reflect the quality of these relationships. Stated differently, while more close relationships with prosocial family members might predict less criminal involvement (e.g., Bales & Mears, 2008; Mowen & Visher, 2016; Wakefield et al., 2016), if those family members are involved in illegal activities, these relationships may instead increase a person's likelihood of criminal involvement, similar to the negative impact of pro-criminal peers.

Dynamic factors (i.e., criminogenic needs) being directly related to criminal behavior and recidivism is a foundational supposition of the RNR model. That is, the Need principle states that people must have their criminogenic needs identified using valid and reliable assessments, and subsequently receive rehabilitative treatments that address those treatment needs (Bonta & Andrews, 2007). Moreover, this framework makes a distinction between static and dynamic factors wherein static risk factors are important for predicting recidivism and dynamic needs are important for classification and informing risk reduction plans (i.e., risk assessment vs. risk reduction; see Skeem & Monahan, 2011). Early risk assessments focused exclusively on static factors (considered second generation actuarial risk assessments, e.g., Burgess, 1936), such as the Salient Factor Scale used to measure risk in the present study (see Hoffman & Adelberg, 1980). In contrast, third and fourth generation risk and need assessment tools include both static and dynamic factors. Examples of common assessment tools used today include the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS; Northpointe Institute for Public Management, 2015), the Level of Service/Case Management Inventory (LS/CMI; Andrews et al., 2004), the Level of Service Inventory-Revised (LSI-R; Andrews & Bonta, 2000), the Ohio Risk Assessment System (ORAS; Latessa et al., 2010), and the Wisconsin Risk and Need Instrument (WRN; Eisenberg et al., 2009).

The validity of these instruments has been well documented, and studies have generally found that global risk scores (i.e., scores accounting for both static and dynamic factors) are correlated with recidivism (Andrews et al., 2006; Girard & Wormith, 2004; Kelly & Welsh, 2008; Latessa et al., 2010; Vose, 2008; Vose et al., 2008). However, there has been much debate regarding the incremental and predictive validity of dynamic factors; namely, whether dynamic factors are able to predict recidivism above and beyond standard static factors (e.g., criminal history, age, sex). In fact, many studies have reported non-significant relationships between dynamic factors and recidivism (Austin, 2006; Austin et al., 2003; Baird, 2009; Dowdy et al., 2002; Duwe, 2014; Flores et al., 2003; Morgan et al., 2013). For example, Austin (2006) found that among 1,006 individuals recently released from prison, only 11 of the 54 LSI-R items were significantly associated with recidivism and that including dynamic factors led to over-classifying individuals as high risk. As noted above, this study highlights the value of using dynamic factors as predictors.

The current study also adds to this body of literature by demonstrating the predictive validity of criminogenic risk factors by examining a 25-year post-release period. These results support the need to assess criminogenic needs at intake so that proper treatment can be provided as a means of improving desistance over time. While static factors are associated with recidivism in the short-term (e.g., Benda et al., 2001; Central Statistics Office, 2016; Worling, 2001), criminogenic treatment needs may be what discerns between people who do, and do not, return to custody in the long-term. This is to say, the association between static factors and criminal involvement may be best explained in terms systemic inequities in education, healthcare, and community support experienced by people who are considered “high risk.” In the short term, static factors may provide a means of assessing a client’s risk for recidivism in that they are reflective of their access to services in the community. For this reason, relying on static factors in determining an individual’s risk of recidivism may not be reliable and could inadvertently contribute to systemic biases in the justice system. Alternatively, addressing criminogenic needs during periods of incarceration, while implementing programs supporting the continuation of services during the reentry period, could allow clients a way to overcome systemic barriers precluding access to necessary treatments in the community and ease the post-release transition period.

Future Directions

The relatively limited sample size for this study, combined with the number of deaths that occurred over the 25-year follow-up, meant that the cell sizes for some of the comparisons were small and therefore under-powered. The all-male sample may also limit the generalizability of findings to justice-involved females. Historically, females are underrepresented in samples recruited from this population (Ornella, 2020), and this warrants intentional changes to recruitment strategies in future studies to understand how these factors may differ in terms of their predictive utility among females. For example, studies have shown that justice-involved females differ from males in that they are less likely to commit violent crimes (Gilfus, 2002; Greenfeld & Snell, 1999), more likely to be convicted of drug offenses (James, 2004; Willis & Rushford, 2003), more likely to have experienced physical and sexual abuse (Dichter & Osthoff, 2015; Gilfus, 2002; Harlow, 1999), and are more likely to serve in primary caregiver roles (Glaze & Maruschak, 2010; Margolies & Kraft-Stolar, 2006; Mumola, 2000). Likewise, substance use and personal/emotional problems appear to be greater predictors of criminal behavior for females than males (Olver et al., 2014). It should also be noted that criminal records are inherently fallible, and do not necessarily accurately reflect the amount of criminal activity a person is involved with, but rather the number of times they have been caught engaging in criminal activity. Specific to the current investigation, records were only available within the state of Texas, and thus do not include arrests or incarcerations that occurred in other states. Future studies in this area may seek to supplement state-level criminal records with data from federal agencies so that arrest and incarceration data can be documented for accurately.

Another noteworthy consideration when interpreting this study's results is that the in-prison therapeutic community treatment represents only one treatment modality. Furthermore, since the treatment program was conducted in 1995, it may not be representative of modern treatment programs. Additionally, the aftercare completion distinction in the present study may present inherent biases given that participants who were reincarcerated were included in the group considered to have dropped out of the aftercare program. This could have artificially inflated recidivism rate among those who dropped out of the aftercare program when compared to those who completed it. Succeeding investigations should evaluate the effectiveness of completing aftercare programs on long-term recidivism, while being mindful of the importance of avoiding compulsory aftercare and controlling for reincarceration prior to the anticipated aftercare completion date.

Finally, this study relied on the RNR model as a theoretical framework in formulating hypotheses around the effects of treatment receipt, aftercare completion, and risk classifications on recidivism, as well as selecting measures of dynamic factors. The RNR model has been criticized for its lack of focus on protective factors and desistance, which could offer other important insights into relevant factors that reduce a person's risk for recidivism (e.g., Polaschek, 2012; Serin et al., 2016). Scholars have argued that, rather than relying on the RNR model's deficit-based framework, there should be a movement towards a strengths-based approach (Rogers, 2000; Ward & Brown, 2004). For example, such an approach may instead emphasize a client's hope and motivation (LeBel et al., 2008), sobriety (Walters, 1998), military service (Sampson & Laub, 1992, 2005), belonging to a social group (Farrall, 2004), and strong social ties (Rex, 2002). Furthermore, available baseline data did not include direct measures of each of the seven criminogenic needs, and therefore measures were selected that were thought to best capture the indicators of five criminogenic needs. While the RNR model does not offer guidance on the best measures of each of the criminogenic needs, studies should intentionally select measures a priori that more directly assess criminogenic needs. Ideally, future studies could include multiple data collection points throughout the follow-up period (i.e., repeated measures), beyond relying solely on criminal records. Including these measures as time-varying covariates would help to better understand how changes in criminogenic needs over time affect recidivism rates.

Conclusion

This study evaluated the importance of matching treatment intensity to clients' criminogenic needs; specifically, reserving intensive services for high-risk people. Results from the present study highlight the need for providing less intensive treatment options to low-risk clients. In addition, aftercare completion had a significant impact on recidivism rates for clients of all risk levels, emphasizing the importance of policies and programs intended to engage clients in aftercare programs following release back into the community. Criminogenic needs (e.g., risk-taking, pro-criminal friends, alcohol dependence) prospectively predicted long-term recidivism risk while controlling for static factors. This further underscores the importance of identifying these treatment needs related to reoffending in order to provide appropriate evidence-based services during incarceration and following release as a means of improving client-level outcomes nationwide. Results suggest a combination of in-prison therapeutic community treatment in tandem with community aftercare programs are most effective at preventing recidivism for high-risk persons.

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ABSTRACT

25-YEAR OUTCOMES OF AN IN-PRISON THERAPEUTIC COMMUNITY
IN TEXAS

by Amanda Lee Wiese, M.S., 2022
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This study evaluated whether in-prison therapeutic community treatment, risk classification (High vs. Low), and aftercare completion were prospectively associated with time to first arrest following release from prison. Moreover, this project established a predictive algorithm of reincarceration using multilevel modeling to identify variables that can be targeted during treatment to decrease reincarceration rates. Based on the Risk-Need-Responsivity model, measures of the criminogenic needs (i.e., family relationships, pro-criminal attitudes, antisocial personality pattern, substance use, and social supports for crime) were compared to static risk factors in terms of their added predictive utility in modeling long-term recidivism trajectories. Results can be used to inform the field's current understanding of in-prison therapeutic communities on recidivism and ways to optimize client selection and the treatment continuum are discussed.