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A SIMULATION ANALYSIS OF ANALYTICS-DRIVEN COMMUNITY-BASED RE-INTEGRATION PROGRAMS

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ABSTRACT

We develop a data-driven simulation model in partnership with Tippecanoe County Community Corrections to evaluate assignment policies of reintegration programs. These programs are intended to help clients with their transition back to society after release, with the goal of ending the "revolving door of recidivism." Leveraging client-level and system-level data, we develop a queueing-based network model to capture the movement of clients in the system. We integrate a personalized recidivism prediction to capture heterogeneous risks, along with estimated effects of reintegration programs from literature. Using simulation, we find that the largest benefit is achieved by implementing any kind of re-integration program, regardless of assignment policy, as the savings in the societal and re-incarceration costs (from recidivism) outweigh program costs. Assignment policy based on predictive analytics achieves a 1.5-time larger reduction in recidivism compared to current practice. In expanding capacity, greater consideration should be given to investing in analytic-driven program assignments.

1 INTRODUCTION

The overuse of incarceration in the United States and the lack of social and community support for offenders leads to a "revolving door" in criminal justice system. Recidivism creates a cycle of incarceration that essentially removes an entire subpopulation from society and leads to generational criminalization (Adams 2020). From the Bureau of Justice, 68% of all inmates released from prison are re-arrested within three years and 50% end up back in prison or jail (Alper et al. 2018). Many repeat offenders are incarcerated due to non-violent crimes associated with Substance Use Disorder (SUD). From the Bureau of Prisons 2019 report, 46% of prison inmates are drug offenders (Federal Bureau of Prison. 2021), around 67% of inmates have substance use disorder (James and Glaze 2006), and 85% of inmates have either been convicted for drug offenses or have an active substance use disorder (National Institute on Drug Abuse). Further, drug offenders have a three year re-arrest rate of nearly 67% (Langan and Levin 2002).

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The large influx of non-violent drug offenders and SUD sufferers, combined with high recidivism rates, has contributed to the national crisis of jail and prison overcrowding; 44% of states have prison populations in excess of 100% capacity and 63% of states have prison occupancies over 90% (Carson and Anderson 2015). To mitigate mass-overcrowding, many states have initiated efforts to reduce recidivism such as California's Substance Abuse and Crime Prevention Act (SACPA); New York's Drug Treatment Alternative-to-Prison program (DTAP) and Texas' Bexar County Jail Diversion Program. These programs steer non-violent drug offenders to supervision and treatment programs instead of jail/prison and have had promising results: SACPA - 33% decrease in new drug arrests; DTAP - 60% reduction in re-incarceration, Bexar - 1,700 diversions saving ∼$4-5 million (Belenko et al. 2013; Johnsrud 2004).

The three components of the Bexar program are (1) diverting SUD sufferers to treatment and support programs before they are arrested and imprisoned, (2) identification of candidates for jail-diversion, (3) providing continuing services after release from prison (Johnsrud 2004). These community-based components have been adopted in many correctional facilities in the country, including our community partner in Tippecanoe County, IN. In this work we analyze these three components within a simulation model to determine the impact of adoption and means of implementation on societal recidivism risk and costs. Specifically, we study how to leverage and implement these resources in a heavily constrained environment. For example, in Tippecanoe County, IN, where our community partner is located, the annual county funding for community corrections programs makes up around 4% of the total funding for the Sheriff's department (Tippecanoe County Budget 2019).

2 LITERATURE REVIEW

Previous research has extensively used a variety of modeling techniques to improve data-driven decision making in resource intensive contexts with potential customer returns, such as readmission in healthcare setting (Chan et al. 2012; Helm et al. 2016; Shi et al. 2021).

However, the literature on the use of operations tools in the context of criminal justice system is scarce. Given the scarcity of resources in correctional settings and importance of targeting available resources to offenders who benefit the most, using simulation models to evaluate the impact of a policy prior to its implementation is critical (Taxman and Pattavina 2013). Usta and Wein (2015) is one of the few papers that used simulation for policy evaluation in this context. The authors developed a simulation model of the LA County jail system to address jail overcrowding. They integrated a risk-based prediction tool for estimating the probability of recidivism and failure to appear in court into a queueing-based simulation, through which they assessed several combinations of pretrial release and split sentencing policies to optimize recidivism rate and jail overcrowding. Their policy simultaneously reduces the recidivism rate and the mean jail population by 7% and 20%, respectively. Based on this simulation model, Master et al. (2018) used queueing theory to develop analytical solutions for the same problem. Our paper uses a similar methodology as Usta and Wein (2015) that integrates a recidivism risk prediction model into a queueing-based network. However, our focus is on Community Corrections, whose clients have different characteristics and different reintegration options compared with jail or prison. Further, we focus on evaluating the capacity of different services provided by community correction and compare different policies in allocating resources for reintegration programs.

One important component of our model is the recidivism prediction. Zeng et al. (2017) compare popular machine learning methods to predict recidivism rate using a public database from the US Department of Justice. Their results show that many black-box methods such as stochastic gradient boosting tree produces accurate (but not interpretable) predictions, whereas methods designed for interpretability produces less accurate result. They propose a Supersparse Linear Integer Models (SLIM) to produce accurate and interpretable scoring system. In our paper, we use the logistic regression model, which is interpretable by nature, and show that the accuracy is comparable with those reported in Zeng et al. (2017). Recent papers such as Wang et al. (2020), Desmarais (2020) emphasize the importance of developing interpretable, accurate, and fair recidivism risk prediction tools. Additionally, the majority of the clients in community corrections suffer from SUD, and opioid use disorder in particular. Broome et al. (1996), along with others, highlights factors that are predictive of recidivism, such as demographics (gender, age, and education), previous arrest status, and number of overdoses in the individual's social network (Sage Crosier et al. 2017; Chen et al. 2020). Ellis et al. (2019) shows that these factors in predicting risk of opioid dependency are also informative when predicting recidivism.

3 CONTEXT, DATA, AND DESCRIPTIVE ANALYSIS

3.1 Community Corrections Network

Figure 1 shows the transition diagram for offenders' interactions with the network of criminal justice system resources. We model the impact of Community Corrections' (CC) services (Work Release and Monitoring) and reintegration programs applied at Monitoring and Home on recidivism and cost.

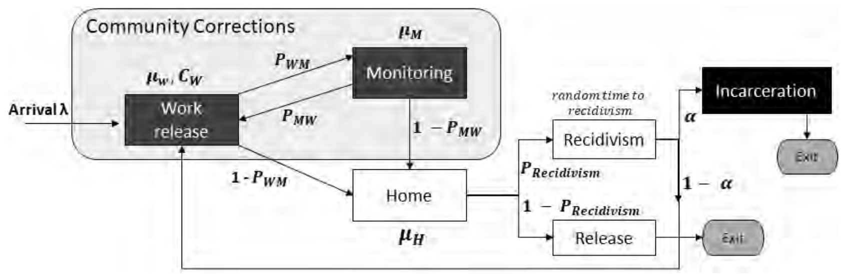


Figure 1: The transition diagram for the network of interactions with the criminal justice system and the cycle of recidivism. λ denotes arrival rate, μ_i denotes the service rate at stage i, C_W denotes the capacity at Work Release (W), P_{ij} denotes the baseline transition probability from stage i to stage j, and α denotes re-incarceration probability after recidivism.

Clients are typically sent to community corrections as part of a jail diversion program, where a jail sentence is replaced by time in community corrections, or are released from jail/prison to community corrections as a step-down measure to aid in reintegration into society. At Work Release, clients are confined to a residential suite, but allowed to leave for work, medical and mental health appointments, and other essential activities. This service represents a high level of supervision. After work release, clients are either released or enrolled in a secondary level of supervision, which we refer to as Monitoring. Monitoring includes both *home detention*, where a client is confined to their home except for essential activities and must check in regularly with Community Corrections, or *day reporting*, in which client movements are less restricted but they must also regularly check in. If Work Release is full, clients are sent to Monitoring. Upon discharge from Work Release or Monitoring, the client may transition to another service or be released home. Clients released to home may experience recidivism (or violation), with probability $P_{recidivism}$, and be incarcerated, with probability α, or returned to Work Release, with probability $1-\alpha$, depending on the severity of the infraction. The recidivism probability is estimated using client-level data from TCCC; see Section 4.

3.2 Dataset

The data set was obtained from Tippecanoe County (Indiana) Community Corrections (TCCC). This study was approved by Purdue IRB (IRB-2019-53). The data set contains 56,389 unique individuals who have interacted with TCCC within the past 25 years; however, we only include data after 2010 since some fields were not recorded prior to 2010. Client data includes demographics and history of involvement with the center. Demographic features include age, race, gender, registered sex offender status, violent offender status, gang member status, homeless status, license status, employment status, and highest education level. We categorize the race features into Caucasian, Hispanic, African American, and Other. We categorize the highest education level into three groups: No High School Diploma, High School Diploma, Some College or College Degree. The database also recorded dates of individuals activities including results of drug screenings, dates of appointments with case managers, and dates of case opening and closure. In our study, we include only clients between 18 and 80 years old. Features with missing information are labeled "unknown." Table 6 in Online Appendix A provides a summary of features and descriptive statistics.

3.3 Recidivism Rate

Following the literature, we define the recidivism as an offense that occurs between 7 days and 3 years from the prior release. Recidivism was identified in the dataset through a new case opening or a jail event following a previous case for the same individual within the time window. If the event was less than 7 days, it is considered as the same case for this individual. For individuals with multiple recidivism events, we treat each event separately in the prediction analysis. However, when we split the data into training and testing data, we put all recidivism events from the same individual either in the testing set or the training set. This avoids information leak between the training and testing data. The average recidivism rate after 2010 is 21% for community correction clients. Figure 2 shows the histogram for the timing of the recidivism on a monthly basis. Most of the recidivism events happen within one year.

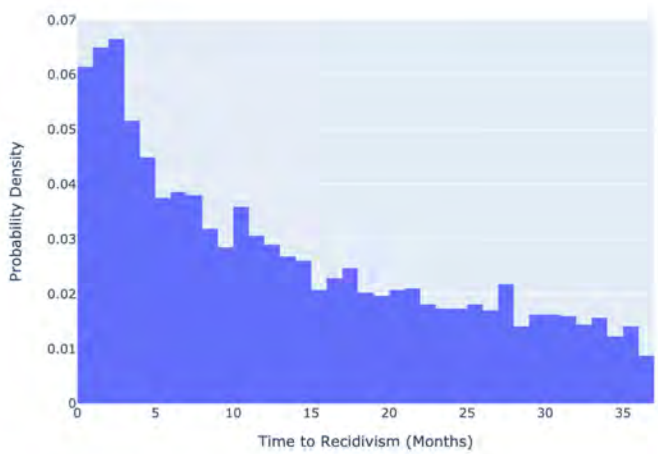


Figure 2: Reported time to recidivism

3.4 Other System-level Parameters

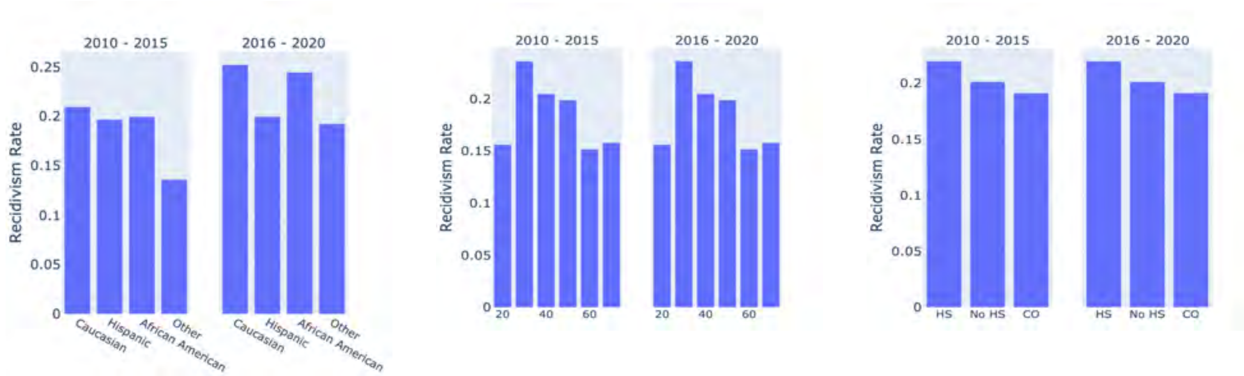
Based on the data from TCCC, we fit exponential distributions to the time that clients spend in Work Release, Monitoring, and home with rates $\mu_W = 0.413$, $\mu_M = 0.23$, and $\mu_H = 0.082$, which corresponds to an average service time of 2.42, 4.34, and 12.20 months. We estimated the baseline (average) network transition probabilities from data as $p_{WM} = 0.48$, $p_{MW} = 0.2$, and $p_{MH} = 1 - p_{MW}$. In our simulation, we adjust these probabilities for individual clients based on their risk level. Clients with higher risk, r, are less likely to be released to Home after Work Release and more likely to commit a violation in Monitoring and return to the Work Release. Thus, we define P_{MW} and P_{WM} as linearly increasing functions of r.

4 RECIDIVISM RISK PREDICTION

In this section, we apply logistic regression to predict recidivism risk after completing the community corrections program based on client risk factors as an input to our simulation model.

4.1 Relevant Features

Figure 3 plots the recidivism rate for three features that are strongly correlated with recidivism. We can observe high recidivism rates in the following categories: (i) Caucasian; (ii) age 30-50, and (iii) clients with only a high school diploma. We also find strong correlation between gender/employment status and recidivism rate, which is shown in Figure 5 in Online Appendix A.



(a) Recidivism rate by race/ethnicity (b) Recidivism rate by age (c) Recidivism rate by education

Figure 3: Variations in recidivism rate by different features. For the education level, "HS" stands for high school, "NoHS" stands for without high school, "CO" stands for college degree and above.

4.2 Predictive Analysis

We use a 70/30 random split for training and testing for estimating our logistic regression model. We place all recidivism events from the same individual in the same set, either training or testing. During training, we apply the downsampling technique to ensure that the model was not biased towards the over-represented indicator. This is important because the majority of individuals did not recidivate. To make sure that the results are robust to the random splitting of the data, we repeat this procedure for 100 repetitions. Table 1 summarizes the estimated coefficients for the main features and their p-values. The coefficients of most features are statistically significant and the signs of the estimated coefficients generally agree with findings in the literature. The average out-sample area under the curve (AUC) score is 0.75 (SD = 0.003). This AUC is comparable with existing prediction tools for recidivism; e.g., Zeng et al. (2017).

5 SIMULATION MODEL OF THE CYCLE OF RECIDIVISM

In this section, we specify how we calibrate each component in the simulation model based on the transition diagram introduced in Section 3. We then introduce our simulation setup and the main performance metrics evaluated. We conclude the section by presenting model validation results.

5.1 Model Specification and Calibration

Process Flow. the with rate $\lambda = 57$ arrivals per month based on the TCCC historical data. We find that the inter-arrival time distribution closely follows an exponential distribution. Upon generating an arrival, we randomly sample a feature vector from the historical data and assign this vector to the arriving client. This feature vector determines the baseline recidivism risk for this client; see more details on calculation of this risk below. Service times are generated according to exponential distributions with rates μ_i for $i \in \{W, M, H\}$. Upon leaving station i, a client transfers to station j with probability $p_{i,j}(r) = p_{ij} + r(1 - p_{ij})$, where $p_{ij} \in \{p_{WM}, p_{MW}\}$ is the baseline transition probability. Service rates and the baseline transition

Table 1: Logistic regression coefficients. The baseline covariates for race, employment status, education level, and licence status are: race_African American, employmentStatus_Unknown, HighestEducationLevel_Unknown, and licenseStatus_Unknown, respectively.

Covariates	Coeffcient	P-Value
age	-0.0203	0.0000***
num_prior_violations	1.6951	0.0000***
race_Caucasian	-0.1774	0.0021***
race_Hispanic, Latino	-0.2156	0.0363**
race_Other	-0.3354	0.0078***
gender_Male	-0.0894	0.0746*
registeredSexOffender_True	-0.4036	0.0758*
violentOffender_True	0.3602	0.0000***
gangMember_x_True	0.1247	0.3807
homeless_True	0.6977	0.0000***
DNACollected_True	0.8465	0.0000***
employmentStatus_Full-Time	1.9106	0.0000***
employmentStatus_Part-Time	1.7344	0.0000***
employmentStatus_Unemployed	1.8086	0.0000***
HighestEducationLevel_High School Diploma	1.6131	0.0000***
HighestEducationLevel_No HS Diploma	1.6316	0.0000***
HighestEducationLevel_Some College+	1.4484	0.0000***
licenseStatus_Not Suspended	0.7892	0.0000***
licenseStatus_Suspended/Restricted	1.0841	0.0000***
Intercept	-4.8956	0.0000***

$***P < 0.01, **P < 0.05, *P < 0.1$

probabilities are given in Section 3.4. When a client is sent home, we generate a recidivism event according to a Bernoulli random variable with probability being the client's risk upon discharge. If a recidivism event occurs, we generate the time of recidivism based on the empirical distribution shown in Figure 2 and whether the event results in Incarceration or return to Work Release with probability α. After Incarceration or Release, the client exits the system.

Capacity. Work Release has a capacity C_W. Clients arriving to a full Work Release station are sent to Monitoring. Monitoring or Home do not have capacities on number of clients (since clients are not housed in a TCCC facility), but instead have capacities C_M and C_H for the re-integration programs available at these stations; see "Reintegration Program" part below.

Costs. We include three costs in our simulation model: Incarceration, Work Release/Monitoring, and treatment/reintegration programs. Incarceration costs on average \$1,680 per month per individual, and we assume offenders spend an average of 54 months in jail/prison based on Indiana data. Work Release and Monitoring costs are estimated from TCCC participants handbook and interviews with the managerial team at TCCC. We estimate each client in Monitoring or Work Release costs around \$730 per month. National Drug Intelligence Center (2011) estimates that cost of providing drug abuse treatment at correctional facilities is about 15% of incarceration costs; thus, we estimate cost of providing reintegration programs for each client to be \$250 per month.

Recidivism Risk. When clients participate in Community Corrections (CC), they experience a reduction from their baseline recidivism risk, which is well documented by the IDOC and the academic literature. Section 4 estimates the post-CC recidivism risk. To parameterize our simulation model, we develop the following adjustment to estimate a client's (baseline) risk prior to entering CC.

Let $\sigma(\gamma, \mathbf{x}_i)$ denote the logistic function estimated from Section 4, where $\mathbf{x}_i$ is the feature vector for client i, and γ is the coefficient vector given in Table 1. Let $\bar{\sigma}(\gamma)$ be the average predicted recidivism risk across all historical clients. We estimate the baseline risk for client i with risk factors $\mathbf{x}_i$ as $r_{\mathrm{b}}(\mathbf{x}_i) = \bar{r}_{\mathrm{b}} \cdot \sigma(\gamma, \mathbf{x}_i)/\bar{\sigma}(\gamma)$, where $\bar{r}_{\mathrm{b}}$ is the population average recidivism risk for offenders not enrolled in CC. IDOC data indicates that, for Tippecanoe County, $\bar{r}_\mathrm{b} \approx 0.341$. For a client receiving service from station $j \in \{W, M\}$, we assume his/her recidivism risk is reduced by $(1-\rho_j)$, i.e., the post-service risk becomes $r_j(\mathbf{x}_i) = \rho_j \cdot r_\mathrm{b}(\mathbf{x}_i)$. We estimate $\rho_W = 0.705$ and $\rho_M = 0.936$ from the IDOC data; see Online Appendix B for details.

Reintegration programs. In Monitoring and Home, clients can be assigned to re-integration programs. These programs are third-party services offered outside TCCC mainly targeting people with SUD; e.g., counseling, support groups, relapse prevention, therapy, and medical assisted treatment (MAT). Studies find a heterogeneous effect of such programs on recidivism, with high-risk clients experiencing little or even no benefit (Evans et al. 2011) and lower risk clients experience small reductions in absolute risk since their baseline is already low. To capture this phenomenon, we define a reintegration efficacy function

$$f_e(r) = \min\left\{\frac{a \cdot r}{b - c \cdot r^2}, r\right\} \tag{1}$$

where r is the recidivism risk at a station without treatment, which can be calculated using the functions, r_j along with the baseline risk defined above. Figure 4 shows our parameterized efficacy function.

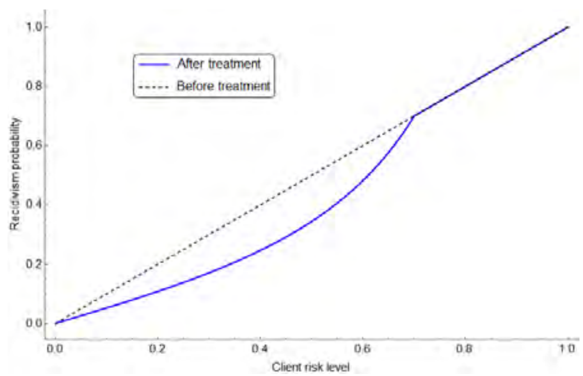


Figure 4: Reintegration efficacy function

The structure of the efficacy function was designed to generally follow trends found in the literature as follows. First, lower risk offenders participating in treatment reduced their recidivism risk by a factor of around two relative to high-risk offenders. This is represented by Eq. 1 using the parameters we estimated ($a = 1.0549, b = 2.03, c = 1.99$), which were also used to draw Figure 4. Specifically, the average risk reduction for high risk clients (between 0.6–0.7) is 0.067, whereas the average risk reduction for low risk clients (between 0.3–0.4) is 0.143, or about twice that of the high risk clients. High-risk offenders were more likely to drop out of programs, leading to no improvement in risk relative to offenders who did not participate in programs (Evans et al. 2011). We tuned the parameters, a, b, and c within our simulation model based on the treatment volume seen in our data so that the overall recidivism rate from our simulation roughly matches the value from our data (21%) using the "Random" assignment policy in Table 4, which approximates the current policy. Applying the risk curve in (1) to our data set gives an average treatment effect of around 34% reduction in recidivism, which is in the same range as empirical studies such as Evans et al. (2006), that found a 33% reduction in recidivism across a treated population. Thus, we feel that the structure and magnitude of our efficacy function provide a reasonable representation of the impact of reintegration programs.

When a client who was enrolled in the re-integration program enters the home station, he/she has a certain probability q of dropping out the program; otherwise, he/she stays in the reintegration program and occupies the capacity until either release or recidivism. This is to model the fact that patients may drop out of treatment once they leave Community Corrections, as shown in Evans et al. (2011).

5.2 Simulation Methods

We run the simulation until 7,000 clients exit the network, which is equivalent to about 12 years. To evaluate the steady-state system behavior, we start with an empty system and collect statistics after a warm-up period, the length of which is determined by the Welch graphical method (Welch 1981). For each set of experiments, we run 50 replications to calculate the average performance metrics: average number of clients at Work Release and Monitoring, the blocking probability at Work Release (i.e. the probability that a client cannot enter the Work Release program due to the lack of capacity), the recidivism rate, and system costs (treatment cost, incarceration cost, and holding costs). We also report the average case manager case loads, calculated by dividing the total number of clients at Work Release and Monitoring programs by the number of case managers staffed at TCCC.

5.3 Model Validation and Verification

We verify our simulation model using methods suggested by Law et al. (2000). We first run the model under simplifying assumptions such as unlimited capacity in the Work Release and no reintegration programs and compare the simulation results with the known analytical solution. Next, we use the trace technique to verify that each of the simulation modules is operating correctly, i.e., displaying the state of the system after each event and comparing the output with manual calculations to verify the correctness of the simulation logic. Finally, we compare simulation model output with the empirical values for the number of clients in Work Release and Monitoring programs, and post-CC recidivism rate on both the mean and 95% confidence interval. Table 2 shows that the simulation output reasonably matches the empirical metrics.

Table 2: Validation results. Numbers in the square brackets are the corresponding 95% confidence interval.

Performance metric	Actual	Simulation		Relative error
Number of clients at Work Release	108.56 [108.15, 108.96]	109.16	[109.14, 109.18]	-0.6%
Number of clients at Monitoring	361.44 [360.43, 362.44]	350.24	[347.00, 353.48]	3.1%
Recidivism rate	0.210 [0.204, 0.216]	0.225	[0.223, 0.227]	-7.10%

6 TACTICAL AND OPERATIONAL DESIGN OF AN EFFECTIVE COMMUNITY CORRECTIONS PROGRAM

In this section we analyze the impact of program assignment, program design, and budget allocation decisions by performing counterfactual experiments, comparing options along the metrics of client access, reintegration impact, case managers' caseload, total client load, and costs.

Program Assignment. Because of limited budgets and community resources it is not possible to provide a comprehensive suite of reintegration programs to all Community Corrections Clients. We analyze four program assignment policies based on an individual's recidivism risk: random, higher risk first, threshold assignment, and none (no programs). Providing treatment and reintegration programs is relatively new in the correctional system and not widespread, which is why we include no programs in the comparison even though TCCC does provide access to programs.

Program Design. We investigate whether and how much capacity to allocate to continuation of reintegration programs and treatment once a client is released from Community Corrections to Home. One major issue stunting the impact of mental health and addiction treatment programs is the lack of continuity when a patient is discharged from community corrections. High workloads in community health services make it difficult for a discharged client to obtain an appointment with a local provider by themselves. Additional effort is needed by CC to facilitate this continuity. In our study, we quantify the benefit of expanding reintegration programs and improving continuity.

Budget Allocation. TCCC has plans to expand their Work Release and reintegration programs. In this counterfactual, we vary the Work Release capacity and program capacities to investigate how to best allocate budget among different options to minimize recidivism.

6.1 Program Assignment

For the random and higher-risk-first policies, we select a new client for participation either randomly or with the highest risk, respectively, when a unit of program capacity becomes available. For the threshold policy, we only assign clients whose risk falls within the range $[\varepsilon_\ell, \varepsilon_h]$, and we use line-search to find the best threshold range. In our base model (current state), program capacity is set such that programs can accommodate 30% (on average) of CC clients in Monitoring and no programs are offered at home. Programs are not offered in Work Release. When a client enters the home station, he/she has a 70% chance of continuing treatment (if space available) and occupies the capacity until either release or recidivism. Otherwise the client drops out of treatment.

We first present the impact of program assignment policies on department of corrections costs. We then highlight client and Community Corrections metrics that are the main drivers of these costs to better understand the impact of the policies on different participants in the criminal justice system. We categorize these metrics in terms of client-focused metrics, access and reintegration impact, and corrections-focused metrics. Tables 3 and 4 show the impact of the four program assignment policies. A key takeaway from both tables is that the largest benefit is achieved by implementing any kind of re-integration program, regardless of assignment policy. Further, re-integration programs "pay for themselves," with savings in the other cost centers that outweigh program costs. This is encouraging for Community Corrections programs looking to improve recidivism but lacking the resources to invest in advanced predictive analytics.

Table 3: Impact of program assignment on DOC system costs in million dollars (Mean and 95% CI).

Policy	Reintegration Program Cost	Work Release/Monitoring Cost		Incarceration Costs		Total cost	
No Programs	0	4.23	[4.20, 4.26]	12.72	[12.58, 12.86]	16.95	[16.80, 17.1]
Random (current policy)	0.9	4.02 (5%)	[3.99, 4.05]	11.56 (10%)	[11.43, 11.69]	16.49 (3%)	[16.35, 16.64]
High-risk first	0.9	3.93 (8%)	[3.90, 3.96]	11.27 (13%)	[11.15, 11.39]	16.10 (5%)	[15.97, 16.23]
Threshold (0.17, 0.7)	0.9	3.89 (9%)	[3.87, 3.91]	11.15 (14%)	[11.05, 11.25]	15.95 (6%)	[15.83, 16.07]

Note: Numbers in parentheses show percent reduction relative to No programs.

However, the threshold policy does provide more significant gains over the current state, achieving a 1.5 times large reduction in recidivism; high-risk first does marginally better than random. Even more encouragingly, we observe a *Pareto improvement* from the threshold policy – work release and monitoring costs are also reduced – providing potential justification and ROI for investment in analytics, though how these analytics are deployed may merit careful consideration (e.g., threshold vs high-risk).

Table 4: Impact of program assignment on Community Corrections metrics (Mean and 95% CI).

	Access		Reintegration				Client Case Loads		
Policy	Work Release Blocking		Recidivism Rate		Release		CM Case Load	Avg Clients in System	
No Programs	0.560	[0.556, 0.564]	0.245	[0.243, 0.247]	0.755	[0.753, 0.757]	48.3	483	[479,486]
Random (current policy)	0.537 (4%)	[0.533, 0.541]	0.225 (9%)	[0.223, 0.227]	0.775 (-3%)	[0.773, 0.777]	46.0 (5%)	460	[457, 463]
High-risk first	0.524 (7%)	[0.519, 0.529]	0.221 (11%)	[0.219, 0.223]	0.779 (-3%)	[0.778, 0.780]	45.0 (7%)	450	[446, 454]
Threshold (0.17, 0.7)	0.521 (8%)	[0.516, 0.526]	0.216 (13%)	[0.215, 0.217]	0.784 (-4%)	[0.782, 0.786]	44.5 (9%)	445	[441, 449]

Note: Numbers in parentheses show percent reduction relative to No programs.

In Table 4, we examine the main drivers of the cost savings and highlight the personal and societal impacts. The primary financial and societal benefits from reintegration programs come from reduced recidivism. While programs clearly reduce recidivism, perhaps more subtle is the dual effect of these programs. First, note that Work Release is the most effective lever for reducing recidivism, though capacity is tightly constrained. Reintegration programs, though less directly effective than Work Release, increase access to Work Release (see the Blocking column) without the need to invest in additional capacity. This is because, in addition to reducing re-incarceration, programs also reduce repeat visits to Community Corrections. This has a compounding effect on recidivism by expanding the number of clients that can be enrolled in Work Release, thereby reducing risk for more offenders.

Another important aspect of client service quality is the load on case managers. Each client in Community Corrections is assigned a case manager that helps them set their schedules, look for employment, manage a personal budget, among other support services. Case managers often have high case loads that make it challenging to provide personal attention and can contribute to high levels of attrition. Reintegration programs also reduce average case load (CM Case Load column) and system workload (Avg Clients in System column) by up to 9%, freeing up case managers to do their job more effectively and freeing budget to hire more case managers, serve more clients, or implement more programs.

6.2 Work Release and Reintegration Program Expansion

One of the most important decisions for a Community Corrections organization is how to allocate their limited budget among different services. In this section, we explore the impact of different budget allocations between Work Release and reintegration programs both pre- and post-discharge.

We begin by analyzing the continuity of program enrollment after discharge from Community Corrections to Home, which is currently a major challenge. One mechanism to improve continuity being developed by TCCC is to partner with community providers to reserve appointment slots and have case managers actively manage the transition process to community programs. We model this approach by allowing a certain number of clients at Home access to the re-integration program capacity. This capacity is shared with clients currently in Community Corrections so the total program capacity remains the same.

In Table 5, we compare the relative effectiveness of different approaches by increasing: continuity (as described above), Work Release Capacity, and total program capacity. Note that increasing continuity is different than total capacity; continuity allows clients to continue programs from home but still maintains the same overall capacity. Hence, clients discharged home will compete for capacity with those in Monitoring.

Table 5: Impact of increasing continuity, Work Release capacity, and total reintegration program capacity on metrics under random and threshold policies.

		Total Cost (million dollars)			Recidivism			Case Load		
Policy	Capacity	Low	Med	High	Low	Med	High	Low	Med	High
Random	Continuity	16.49	16.43 (0.4%)	16.46 (0.2%)	0.225	0.222 (1.3%)	0.220 (2.2%)	46.0	46.3 (-0.7%)	46.4 (-0.9%)
	Work Release	17.40	16.49 (5.2%)	14.88 (14.5%)	0.238	0.225 (5.5%)	0.201 (15.5%)	48.7	46.0 (5.5%)	41.5 (14.8%)
	Total	16.54	16.49 (0.3%)	16.22 (1.9%)	0.231	0.225 (2.6%)	0.211 (8.6%)	46.8	46.0 (1.7%)	44.6 (4.7%)
Threshold(0.17, 0.7)	Continuity	15.95	15.74 (1.3%)	15.56 (2.4%)	0.216	0.215 (0.5%)	0.210 (2.8%)	44.5	44.5 (0.0%)	44.5 (0.0%)
	Work Release	16.86	15.95 (5.4%)	14.36 (14.8%)	0.229	0.216 (5.8%)	0.193 (15.8%)	46.9	44.5 (5.1%)	40.1 (14.5%)
	Total	16.08	15.95 (0.8%)	15.68 (2.5%)	0.225	0.216 (4.0%)	0.207 (8.0%)	45.3	44.5 (0.9%)	43.8 (2.7%)

Note: Numbers in parentheses show percent reduction relative to Low capacity.

We begin by comparing the three strategy decisions with respect to the random (current) assignment policy and then compare and contrast the results with the threshold policy. We see the greatest decrease in total cost (14.5%) and recidivism (15.5%) by increasing Work Release capacity, which is not surprising since Work Release is the most effective service. However, Work Release capacity is also the most expensive capacity investment so the ROI must be considered. One item that deserves consideration from CC leaders is that case manager case loads are (slightly) increased by continuity. This occurs because the shared program capacity makes programs less available to clients in Monitoring and more likely for them to commit an infraction and return to Work Release, which increases overall system loads. However, continuity is the cheapest and easiest program to implement so a careful cost-benefit analysis should be undertaken.

The threshold policy demonstrates the same pattern as the random policy but with greater percentage improvement, due to its ability to take advantage of additional capacity through more targeted allocation. Specifically, the performance gap between the random and threshold policies grows significantly with increased capacity. Hence, the more budget for capacity expansion, the more consideration should be given to investing in analytics-driven program assignment.

7 CONCLUSION

In this paper we develop a simulation model to evaluate different mechanisms that can be employed by incarceration-alternatives, such as Community Corrections, to reduce recidivism. We specifically study (i) how to assign clients to different re-integration and treatment programs and (ii) how to make budgeting decisions to have the greatest impact on correctional system costs and individual and societal benefit. We find that these two high-level metrics move in the same direction, i.e., what is good for correctional center costs is also good for clients and society. For program assignment, we find significant gains in all areas can be obtained by implementing a carefully designed risk prediction-based threshold assignment policy. Further, we find that budget decisions have an increasing impact in the following order: continuity of programs when clients are discharged from Community Corrections, overall increased capacity for programs, and increased capacity for Work Release. However, the costs of these three options follow the opposite order. Thus, our simulation model can help in further refining these strategic decisions. Finally, as more budget is allocated to any of these three options, the analytics-based threshold policy demonstrates increasing gains across all metrics by more effectively utilizing the additional resources. This suggests that, as community corrections programs consider expansion, additional investment in analytics-based assignment policies may be warranted.

Online appendix is available at: https://web.ics.purdue.edu/~shi178/Criminal_Justice_Winter_Sim.pdf

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