Appendix

1 Detailed Program Process Flow

Figure 1 provides a more detailed version of the one in the main paper. The incarceration-diversion process begins by an eligible probationer being referred to the program, which can be initiated by a judge, probation officer, or public defender. Upon referral the case is assigned to a expert case manager who conducts a comprehensive screening of the individual's demographic information, offense details, criminal history, drug use, and other pertinent factors. Additionally, a risk assessment score is assigned during this screening process. Our current partner employs the Level of Service Inventory - Revised (LSI-R) score.

Based on the screening results, if the individual is deemed suitable for program admission and expresses willingness to participate, the diversion program starts; otherwise, the case may follow alternative pathways, potentially leading to incarceration or going through other correctional routes. For an admitted individual, the case manager then determines the specific program completion requirements that make-up the in-program activities, such as attending substance use treatment programs, cognitive-behavioral therapy sessions, and vocational training. The case manager regularly asseses the individual's progress within the program, which includes risk assessments, drug tests, and more. These assessments guide decisions regarding the individual's program status – whether they should continue in the program, if any adjustments to the requirements are necessary, or if program termination is warranted.

An individual who successfully fulfills all program requirements receives a *Completed* outcome. However, in some cases, individuals may recidivate, committing new crimes while in the program, resulting in their participation in the incarceration-diversion program being *Revoked*. Consequently, they are terminated from the program. Therefore, in the main paper "in-program revocation" refers to the process of removing an individual from an incarceration-diversion program and transferring them back to traditional incarceration or another correctional settings due to non-compliance or other program-related reasons. Additionally, individuals may fail to complete the program for various reasons, such as being transferred to another county or going missing. These cases are labeled as *Not Completed* in the program outcome. Some individuals may exit the program for "unknown" reasons, which we classify as *Other* during the machine-learning training process.

2 More Descriptive Analysis

In Tables 1 and 2 we provide descriptive statistics for other features in our prediction models. Specifically, Table 2 includes the categorical variables in the data set. These variables are for each individual: (i) Risk: their recidivism risk scaled into 3 levels. (ii) AdOffense: name of the offense committed that lead to them being admitted into the program. (iii) OffenseClass: class of the offense. (iv) Pdrug: Primary drug that the individual stated at admission to consume. (v) ReferralReason: reason for referral to the program. (vi) WhoReferred: Role of the person who referred the individual to the program. (vii) Gender. (viii) EmploymentS: employment type at admission . (ix) MaritalS: marital status at admission. (x) HousingS: states the living situation at admission. (xi) MedicaidSt: Medicaid enrollment status at admission. (xii) UniqueAgents: Number of unique agents that saw the person during his LOS. (xiii) FinalProgramPhase: Final program level that the person achieved. (xiv) RewardedBehavior: indicator to whether the persons received any reward during his LOS in the program, and (xv) Sanctions: indicator to whether the person received any sanction during his LOS in the program. Table 1 provides mean and standard deviation for continuous variables in the dataset. These variables are (i) AgeAtEnroll: Age of the individual at enrollment. (ii) CriminalHistScore: ranges from 0 to 30 and its the estimated score of the individual's past criminal history. (iii) and (iv) AvgMVistis (AvgReqMVisits) Average number of actual (required) monthly visits to the individual during their LOS. (v) and (vi) TotalMVistis (TotalReqMVisits): Total number of actual (required) visits to the individual during their LOS.

Table 1: Continuous Covariates Summary Statistics.

Variable	County			
	DuPage $\mu(\sigma)$	Cook $\mu(\sigma)$	Will $\mu(\sigma)$	Peoria $\mu(\sigma)$
AgeAtEnroll	30.5 (9.9)	41.8 (13.1)	33.6 (9.2)	35.5 (11.0)
CriminalHistScore	5.1 (1.6)	17.9 (11.3)	5.2 (1.7)	5.6 (1.4)
AvgMVisits	1.7 (1.0)	0.5 (0.5)	1.5 (0.8)	4.3 (1.9)
TotalMVisits	39.8 (30.5)	11.2 (11.0)	29.6 (20.0)	93.7 (56.2)
AvgReqMVisits	1.6 (1.2)	–	0.0 (0.0)	–
TotalReqMVisits	38.2 (35.3)	–	0.3 (0.6)	–

2.1 Details of the Outcome Prediction

Pre-processing. We apply the following pre-processing and feature selection process: (*i*) Data transformation: log transformation and square root transformation, were applied to enable the model to better understand the relative relationships between data points. (*ii*) Features grouping and outlier elimination: To enhance model performance, we visualized the distribution of unique values for each feature. Features with less than 3 unique values were dropped. For categorical features, we eliminated unique values that represented less than 10 percent of all unique values. For numerical features, we removed outliers using the Interquartile Range (IQR) method. (*iii*) Feature selection: we filtered features based on feature importance score for GBT model. We develop an automated data pre-processing pipeline to perform these three steps.

Hyper-parameters tuning. After data pre-processing, we split the processed dataset into a training set and a testing set in a 9:1 ratio. We applied a stratified splitting strategy to ensure that each class appears in both the training and testing sets in the same proportion. All models are trained using the training set and tested on the same testing set. For hyper-parameter tuning, we implemented stratified k-folds cross-

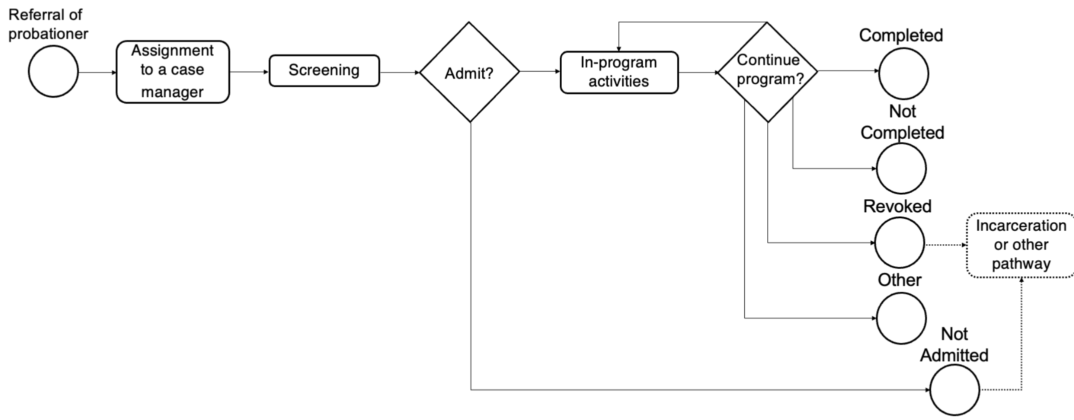


Figure 1: Incarceration-diversion program diagram.

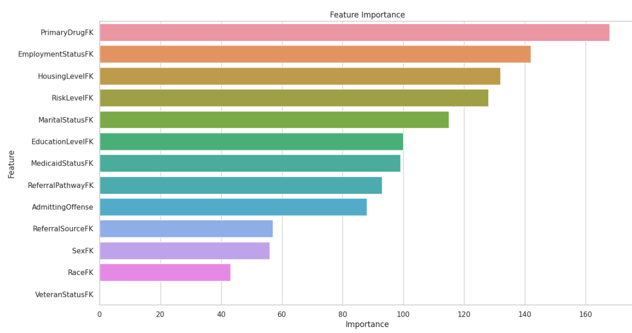


Figure 2: feature importance plot

validation to ensure the models were not overfitting, where each fold must contain the same percentage of samples of each class as the complete set. We tested different values of k with best performance achieved at $k = 5$ for all models. We fine tune hyper-parameters for each ML model to improve the model performance. We automated this tuning process using hyper-parameter optimization frameworks: in our implementation, we used Optuna to optimize hyper-parameters for GBT, Keras Tunner for MLP, and GridSearchCV for LR and DT. We created trials to test different combinations of hyper-parameters, and selected the trial with the best model performance as the final set of hyper-parameters. Specifically, for the MLP, we first tested several possible configurations to narrow down the search space. We then evaluated various hypter parameters (including the number of nodes, layers, optimizers, etc.) to identify the top 50 structures with the best performance using Random Search. We further tuned the learning rates, number of epochs for each of these structures to gain the best out-of-sample performance. We followed the same procedure for other models. Tables 3 to 6 demonstrate parameters of each model, along with tested value and best value.

Table 2: Categorical Covariates Summary Statistics (N/A or Other Categories are Omitted).

Variable	Categories	County			
		DuPage	Cook	Will	Peoria
Risk	Highest	24.3	32.0	2.3	1.0
	High	60.7	26.2	35.1	24.7
	Medium	11.0	15.6	42.1	47.0
AdOffense	Drugs	43.0	67.8	31.7	37.0
	Property	31.1	17.6	52.5	46.3
	DUI	11.1	2.3	3.8	1.0
OffenseClass	Class 4	42.5	–	11.5	20.6
	Class 3	13.5	–	5.7	5.7
	Class 2	16.0	–	5.7	5.1
Pdrug	Heroin	27.0	43.6	32.3	9.5
	THC	18.6	18.5	17.5	21.6
	Coc.Crack	7.8	10.9	21.0	11.6
ReferralReason	Tech Violation	31.2	0.0	12.8	0.0
	3/4 Felon	20.5	70.5	59.2	80.0
	1/2 Felon	9.8	16.5	23.7	14.7
WhoReferred	Prob Officer	64.7	97.3	1.8	0.0
	Judge	32.0	1.3	0.7	91.3
	Pub. Defender	0.6	0.0	75.3	2.8
Gender	Female	25.2	21.3	21.7	19.8
	Male	74.8	77.5	78.2	80.0
EmplymntS	Full Time	49.7	85.7	38.2	6.7
	None	32.3	4.8	59.2	92.0
	Part Time	18.0	9.4	2.7	1.3
MaritalS	Single	86.4	85.6	15.0	22.9
	Married	5.9	7.1	1.8	5.7
	Divorced	4.7	2.3	0.2	1.8
EducationS	HighSchool	40.3	37.2	34.3	13.6
	No HighSchool	32.6	52.4	10.8	12.3
	Some College or Graduated	19.4	3.5	11.8	4.4
HousingS	Friend or Family	62.3	27.9	6.2	17.7
	Own/Rent	29.0	15.5	2.7	11.1
	No Home Reported	5.9	23.9	16.5	70.2
MedicaidS	Yes	23.8	48.4	8.3	3.3
UniqueAgents	4	11.6	2.2	8.6	–
	3	27.9	31.9	22.3	2.3
	2	60.6	65.9	69.1	97.7
FinalProgPhase	Level 3/4	11.1	15.7	32.3	0.3
	Level 1/2	56.5	14.4	22.7	3.1
	Level 0	2.9	35.5	7.0	27.0
RewardedBehv	Yes	4.0	29.1	2.5	1.5
Sanctions	Yes	91.8	99.3	89.8	41.1

Table 3: Gradient Boosting Tree Hyper-parameter Tuning Results.

Parameter Name	Parameter Value	
	Tested	Best
learning_rate	[0.01, 0.5]	0.44
max_depth	[5, 20]	10
lambda_l1	[1e-8, 10]	0.106
lambda_l2	[1e-8, 10]	1.031
num_leaves	[10, 60]	42
bagging_fraction	[0.6, 1.0]	0.612
feature_fraction	[0.6, 1.0]	0.701

Table 4: Decision Tree Hyper-parameter Tuning Results.

Parameter Name	Parameter Value	
	Tested	Best
criterion	gini, entropy	gini
max_depth	[1, 15]	6
min_samples_split	[1e-8, 10]	9
num_leaves	[10, 60]	42
min_samples_leaf	[0.6, 1.0]	2

Table 5: MLP Hyper-parameter Tuning Results.

Parameter Name	Parameter Value	
	Tested	Best
num of neurons in input layer	[12, 512]	20
dense activation function	relu, tanh, sigmoid	relu
number of hidden layers	[1,5]	2
num of neurons per hidden laye r	[12, 512]	45, 20
layer activation function	relu, tanh, sigmoid	relu, sigmoid
dropout rate	[0.0, 1.0]	0.1, 0.1
optimizer	adam, sgd, rmsprop	adam
learning rate	[0.001, 0.1]	0.00399

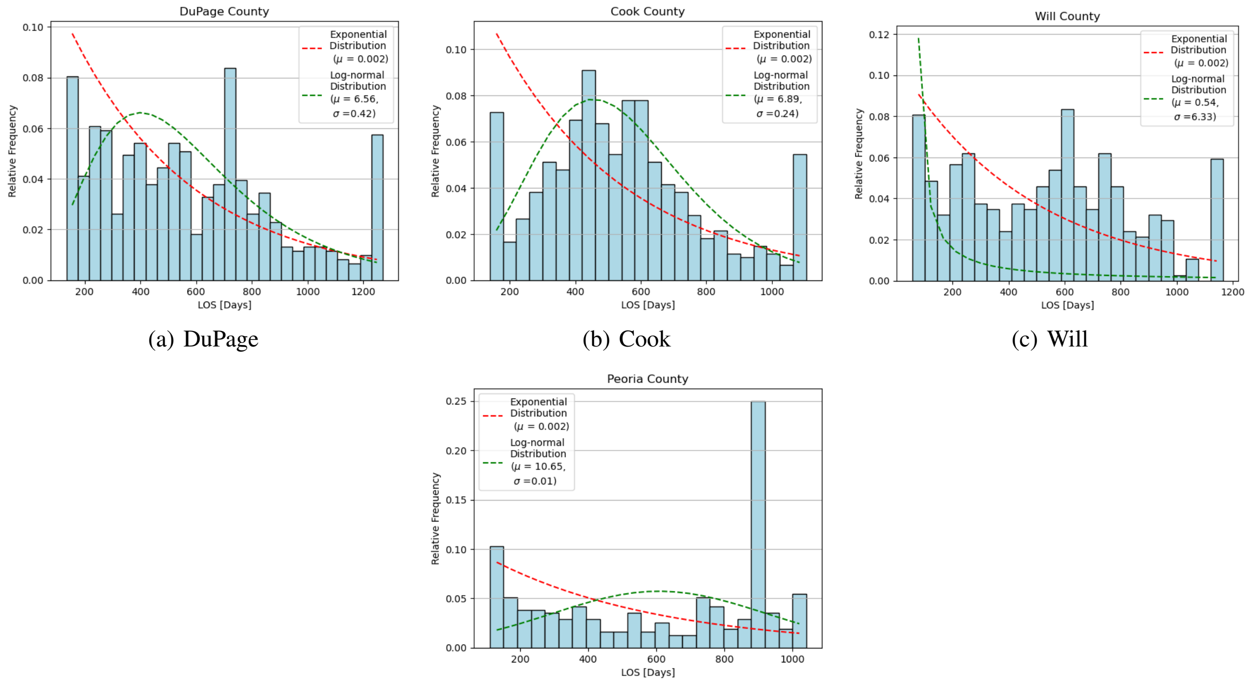
Table 6: Logistic Regression Hyper-parameter Tuning Results.

Parameter Name	Parameter Value	
	Tested	Best
penalty	l1, l2, elasticnet	l1
l1_ratio	[0, 1]	(Not Used)
C (Inverse of regularization strength)	[0.0, 1.0]	0.018
solver	liblinear,lbfgs,saga	saga

2.2 Figures for Arrivals and LOS

Table 7: LOS by Outcome Summary Statistics

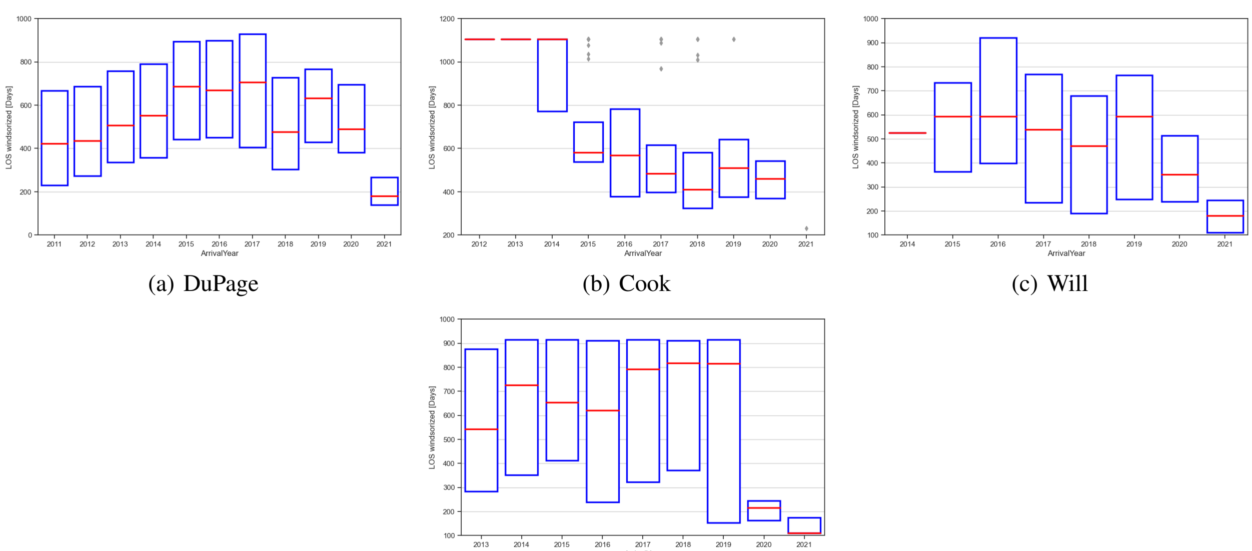
County	Race	LOS yrs. by Outcome Mean (SD)		
	grp.	Com.	Not Com.	Revok.
DuPage (2011-2022)	All	1.6 (0.7)	1.4 (0.9)	1.7 (1.0)
	W	1.7 (0.7)	1.3 (0.9)	1.7 (0.9)
	AA	1.6 (0.8)	1.6 (1.0)	1.8 (1.1)
	H	1.5 (0.7)	1.6 (1.0)	1.7 (1.0)
	OT	1.3 (0.6)	0.5 (0.2)	1.9 (1.1)
Cook (2012-2022)	All	1.5 (0.5)	1.3 (0.8)	1.5 (0.8)
	W	1.8 (0.7)	1.3 (0.4)	1.1 (0.8)
	AA	1.5 (0.5)	1.3 (1.0)	1.5 (0.8)
	H	1.6 (0.4)	1.1 (1.0)	1.6 (0.8)
	OT	1.6 (0.7)	–	0.6 (0.3)
Will (2014-2022)	All	1.9 (0.6)	1.0 (0.9)	1.1 (0.8)
	W	1.9 (0.7)	0.9 (0.8)	1.1 (0.7)
	AA	2.0 (0.9)	1.3 (0.9)	1.2 (0.9)
	H	2.1 (0.7)	0.6(0.7)	1.3 (0.7)
	OT	2.2 (0.8)	1.0(1.4)	2.4 (–)
Peoria (2013-2022)	All	2.3 (0.5)	1.1 (0.7)	1.2 (1.0)
	W	2.2 (0.6)	1.3 (0.8)	1.1 (1.0)
	AA	2.3 (0.5)	1.1 (0.7)	1.3 (1.1)
	OT	2.3 (0.5)	0.8 (0.3)	–



(a) DuPage (b) Cook (c) Will

(d) Peoria

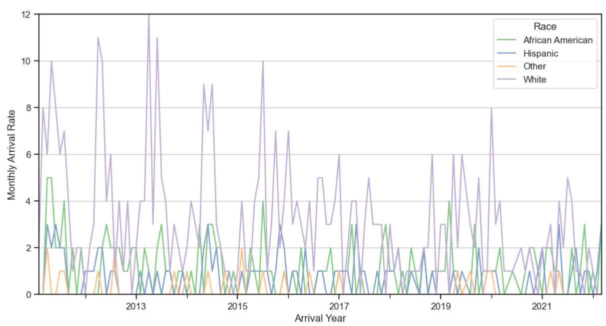
Figure 3: Length of Stay Distributions (Complete Data, Windsorized)



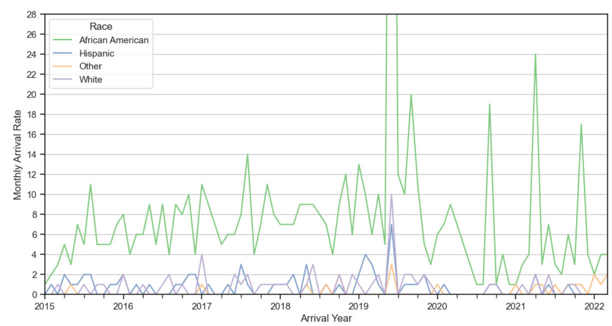
(a) DuPage (b) Cook (c) Will

(d) Peoria

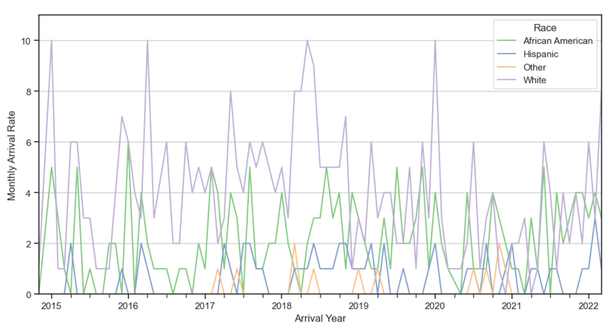
Figure 4: Length of Stay per Year (Complete Data, Windsorized)



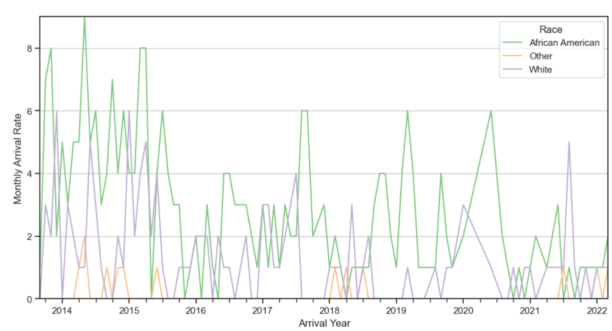
(a) DuPage



(b) Cook



(c) Will



(d) Peoria

Figure 5: Monthly Arrival Rate by Race