Factors That Relate to Successful Post-Incarceration Outcomes for Individuals in Community Justice Programs in Connecticut

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1 Introduction

The Connection is a Connecticut-based non-profit organization that provides support services to individuals experiencing homelessness, struggling with mental illness, or substance use. One of their main services is providing support in social justice rehabilitation for prisoners and probationers to assist them in reentering their communities. Utilizing trauma-informed and person-centric care methods, The Connection works to balance ensuring the safety of a larger community and meeting the needs of the individuals they support (*About*, 2025). As part of their work, they hope to understand the factors that lead to individuals successfully exiting these programs and re-entering their communities. For my capstone project, I will be working with data provided by The Connection to assist them in identifying factors that relate to successful post-incarceration outcomes, including demographic variables, pre-assessed risk levels of recidivism, and criminal thinking profile measures.

1.1 Literature Review

Risk assessment tools are often used to identify the most the at-risk offenders, allowing correctional facilities to provide more support and higher levels of intervention to these offenders (Frisch-Scott & Nakamura, 2022). Risk assessments built with this goal in mind are based on the risk-need-responsivity (RNR) model developed by Andrews, Bonta, and Hodge in 1990. These assessments aim to understand three main things: 1) risk levels, to accurately match offenders with more intensive treatments, 2) any needs that are related to criminal behavior and need to be met, and 3) the offender's learning style and abilities, to accurately align treatment with a style that the offender can learn from (D. Andrews, Bonta, & Wormith, 2011; D. A. Andrews, Bonta, & Hoge, 1990). A large body of historical research supports the success of RNR models in identifying offenders most at-risk of recidivism, especially male offenders, despite some gaps present in this framework and potential issues with some of the studies (D. Andrews et al., 2011; Fazel, Hurton, Burghart, DeLisi, & Yu, 2024; Frisch-Scott & Nakamura, 2022; Vitopoulos, Peterson-Badali, & Skilling, 2012). However, minimal research has been conducted on how risk assessment tools are connected to successful outcomes after prison or for those under probation, a topic this capstone will cover.

Studies have been conducted on the difficulties faced by individuals who attempt to re-enter their communities after serving prison sentences, identifying unemployment, low education, and substance abuse as risk factors for recidivism (Gill & Wilson, 2017). Reintegration into the community has been studied specifically for male offenders, identifying multiple factors that influence successful outcomes, including the utilization of RNR models (Mathlin, Freestone, & Jones, 2024). RNR models are useful especially as they work to meet the needs of each offender, and many individuals who have their needs unmet are likely to recidivate, especially among prisoners that are considered high-risk (Gill & Wilson, 2017; Polaschek, Yesberg, & Chauhan, 2018).

On the other hand, outcomes for probationers have different predictive factors, more often demographic variables. Literature suggests that probation outcomes are influenced by race and gender. White women are the most statistically likely to complete probation, and Black men are most statistically likely to fail probation (Boppre, Sundt, & Browne, 2024; Phelps, 2017; Steinmetz & Henderson, 2016). Those on probation with mental health issues are also more likely to fail probation, and this relationship is moderated by gender (Brooker, Sirdifield, & Parkhouse, 2022; Prost, Higgins, Golder, Logan, & and, 2019). Age is often used as a covariate in predicting successful outcomes, especially with young adults, but evidence is mixed on whether it is a statistically significant predictor (Barnes-Lee, Goodson, & Scott, 2023; Clark, Lerch, Lopez, & Taxman, 2024). To complement this research, my capstone project will utilize a variety of demographic covariates, including race, and age. Gender will not be included as a possible predictor as most participants in the dataset provided by The Connection identified as male.

Demographic variables are also of interest when identifying outcomes for prisoners. A large body of literature that supports a positive relationship between mental health problems and/or a history of traumatic experience and the probability of recidivism (Houser, Vîlcică, Saum, & Hiller, 2019; Ryan, Williams, & Courtney, 2013; Sadeh & McNiel, 2015). Race and ethnicity also change how successfully individuals can reenter their communities post-incarceration. Black and Hispanic offenders receive harsher sentencing than white offenders (Camplain et al., 2020; Lehmann & Gomez, 2021), and are more likely to be unemployed after leaving prison, which can lead to higher levels of recidivism (Harding, Morenoff, Nguyen, & Bushway, 2018; Kolbeck, Bellair, & Lopez, 2022).

Outside of demographic factors, multiple criminal thinking behaviors have been found to have a positive relationship with recidivism, such as negative attitudes toward authority, positive attitudes toward deviance, and attachment to criminal identity (Walters, 2016). The eight criminal thinking profile measures utilized by The Connection have been linked to higher levels of participants failing to complete community justice programs post-incarceration (Mitchell, Tafrate, Hogan, & Olver, 2013). Those with higher levels of these criminal thinking profile measures have also been found to be more resistant to treatment and community justice programs, which could relate to their lower levels of success in these programs (Best, Day, Campbell, Flynn, & Simpson, 2009; Garner, Knight, Flynn, Morey, & Simpson, 2007).

This capstone will complement the current literature on post-incarceration outcomes by identifying multiple possible predictors of successful exits from community justice programs, specifically those run by The Connection. By focusing on a specific sample, the results of this capstone will be directly applicable to The Connection's work and will help them create more targeted support programs.

1.2 Research Questions

To guide this research, there is one main research question, which involves three sub-questions:

1. What factors relate to successful and not successful outcomes for people in rehabilitation programs at the Connection?
   (a) What is the relationship between risk of recidivism, as measured through the Ohio Risk Assessment Survey, and successful and not successful outcomes?
   (b) How do criminal thinking profile measures, suicide and homicide risk, and demographic variables relate to successful or not successful outcomes?
   (c) Do success rates differ at each of the programs run by The Connection? If so, which programs have the most success and why?

2 Methodology

2.1 Sample

The data used in this capstone were provided by The Connection, and include individuals who have either previously spent time in prison ($N = 1235$) or under supervision while in their communities ($N = 105$).

1. *SRT, RT, and CST Assessment Scores*

   Three datasets in this project look at recidivism risks based on the Ohio Risk Assessment Tool (ORAT) developed by Latessa, Smith, Lemke, Makarios, and Lowenkamp (2009), each with a modified set of questions designed to fit a certain population of offenders. The three that will be used in this capstone project are the Reentry Tool (RT), used for clients that have been in prison for four or more years, the Supplemental Reentry Tool (SRT), used for clients that have been in prison for less than four years, and the Community Supervision Tool (CST), designed to measure risk of recidivism in individuals that are not in halfway houses, have been in the community for more than a year, and require supervision. The CST was used on 222 individuals, the RT on 607, and the SRT on 1702.

These tools were developed using the RNR model for risk assessment, and all three of the risk assessments cover various categories of questions that are each scored and utilized to create an overall risk score. The CST includes questions on criminal history; education, employment, and financial situation; family and social support; neighborhood problems; substance use; peer association; and criminal attitudes and behavioral problems. The RT and SRT each cover criminal history; education, employment, and social support; and criminal attitudes and behavioral problems, but the SRT also asks about substance abuse and mental health problems.

2. *Episode Data*

   This dataset includes information on individuals' ages, the program each one stayed at, how long they stayed in days, on the program each individual stayed at, how long they stayed in days, their discharge status, and their living arrangements at admission and discharge. This dataset includes information on 3280 individuals.

3. *Client Data*

   This dataset includes demographic information on the individuals in programs at The Connection. These variables include birth year, biological sex, gender identity, sexuality, race, marital status, religion, primary language, veteran status, and ethnicity. This dataset includes information on 3280 individuals.

4. *Suicide/Homicide Risk Data*

   This dataset includes self-reported information on scores for questions identifying suicide and homicide risk among individuals at The Connection. All variables in the dataset are measured categorically and indicate high, moderate, and no risk for both suicidality and homicidal tendencies. These risk levels were calculated based on individuals' responses to questions adapted from the Columbia-Suicide Severity Rating Scale (Posner et al., 2010), capturing information on the presence and severity of suicidal and homicide behaviors and thoughts. 1912 individuals responded to the suicide risk survey and/or the This dataset includes information on 1912 individuals.

5. *Criminal Thinking Profile Data*

   The criminal thinking profile used by The Connection was developed in response to literature on cognitive behavior therapy and criminal thinking studies (Mitchell & Tafrate, 2012). The dataset includes scores for eight measures of criminal thinking, which were calculated by summing individuals' answers for 65 questions, rated on a 1-4 Likert scale. 2983 individuals responded to the criminal thinking profile questionnaire.

2.2 Measures

The final dataset used in this project includes 1129 unique individuals who participated in community justice programs run by The Connection between 2018 and 2024. However, there are 1340 observations in the dataset as some individuals participated in these programs multiple times or moved from one location to another during the study period. Datasets were matched on both participant ID and event ID variables to ensure information from each time a participant entered the program was kept.

The final variables used in analysis include:

- Risk level of recidivism. Values include low, moderate, and high levels of risk. This measure is based on the Ohio Risk Assessment Tool (Latessa et al., 2009). In the final dataset, 543 (41%) individuals were low risk, 596 (45%) were moderate risk, and 201 (15%) were high risk.

- Race. Values include White, Black, and Other. All other races were collapsed into the Other category due to small sample sizes. 567 (43%) individuals were Black or African American, 427 (33%) were White or Caucasian, and 319 (24%) were another race.

- Criminal Thinking Profile variables. The final eight measures included 1) disregard for others, 2) inability to cope, 3) emotional disengagement, 4) reckless impulsivity, 5) poor judgment, 6) outsourcing responsibility, 7) justifying, and 8) grandiosity. All eight measures are continuous, with higher values corresponding to higher levels of these measures of criminal thinking. Responses ranged from 0, indicating the absence of these criminal thinking behaviors, to 99, indicating a very high level of these criminal thinking behaviors. Average scores were 22 for disregard for others, 12 for inability to cope, 13 for emotional disengagement, 14 for reckless impulsivity, 14 for poor judgment, 7 for outsourcing responsibility, 10 for justifying, and 17 for grandiosity.

- Suicide and Homicide risk. Values include risk and no risk for both variables. The ”risk” category was creating by collapsing values for moderate and high risk, while the ”no risk” category retains its original values. 1293 (96%) individuals had no suicide risk, while 47 (4%) had at least some suicide risk. 1329 (99%) individuals had no homicide risk, while 11 (¡1%) had at least some homicide risk.

- Program name. The five programs included in this dataset are 1) The Eddy Center, 2) REACH, 3) Sierra Center, 4) Roger Sherman House, and 5) The

January Center. The Eddy Center is residential transitional housing focusing on case management services, treating substance abuse, and providing mental health resources. REACH is a short-term supportive housing and case management program that aims to help individuals secure housing and employment. Sierra Center and Roger Sherman House are residential work release programs that provide support with case management, job searches, and education on mental health and substance use. The January Center provides residential treatment services for sex offenders, with specific focus on helping individuals manage their sexual behavior. (*About*, 2025) 329 (25%) individuals were at The Eddy Center, 499 (37%) at REACH, 163 (12%) at Sierra Center, 248 (19%) at Roger Sherman House, and 101 (8%) at The January Center.

- Outcome. Outcome was collapsed into the categories of successful and not successful. Successful outcomes included participants who were marked as successful by administrative staff, transferred, were auto-discharged, and those who successfully completed the program or their treatment. Not successful outcomes included participants who were arrested, escaped, were moved to a medical facility, had their cases brought back to court (i.e. were remanded), or were discharged to a higher level of care.

Other demographic variables of interest were removed from analysis due to large amounts of missing values or low amounts of variation, which prevented them from being effective covariates.

2.3 Models

2.3.1 Logistic Regression with Clustered Standard Errors

In this project, multiple logistic regressions with clustered standard errors will be used as the main method of analysis. Each logistic regression will be run with clustered standard errors to properly account for the possibility of participants appearing in the dataset multiple times, and will be clustered on each participant's ID number. Logistic regressions were chosen as the primary method of analysis because the dependent variable of interest (outcome) was binary.

2.3.2 Machine Learning Models

Machine learning methods that specialize in feature selection were used to expand upon the results of logistic regression models. Feature selection was important in the context of this project because of the large number of variables used in logistic regression. The four feature selection methods used were 1) lasso regression, 2) bidirectional stepwise regression, 3) random forest, and 4) gradient boosting.

1. Lasso Regression. Lasso regresion models function very similarly to logistic regression models, but include an additional parameter (λ) which acts as a penalty term for models that include too many variables. Any variables considered unimportant have their coefficients reduced to zero and all remaining variables are important predictors of the outcome variable.

2. Bidirectional Stepwise. Bidrectional stepwise models begin with a full regression model with all specified variables, and remove any predictors that are statistically insignificant. After removing all of these variables, it then will add back all of the variables it removed one by one until all variables in the model are statistically significant. This method combines backwards and forwards stepwise models to ensure that no statistically significant variables are erroneously discarded.

3. Random Forest. Random forest creates many regression trees, and averages all of the trees, combining them into the best possible tree. Each tree has random combinations of variables, ensuring that all trees are different from one another. Once all trees have been created and averaged, the model uses the strongest combination of trees to predict the outcome variable of interest.

4. Gradient Boosting. Gradient boosting functions very similarly to random forest, but with one key difference. Rather than averaging each weak decision tree, gradient boosting aims to minimize the residuals in the model. Each new tree is created based on the error in the previous tree, eventually identifying the strongest model with the lowest residuals possible.

Each model was run with 10-fold cross-validation, which divided the dataset used for training the model into 10 samples and ran the model on all 10 samples. This approach allows for a better understanding of how the model will work on unfamiliar data. All four methods were compared to a 10-fold cross-validated logistic regression to understand the importance of removing variables from the model.

Unlike for the logistic regression models, data used for analysis included only participants with zero missing values for risk level of recidivism, program, age at admission, criminal thinking profile variables, suicide risk, race, and outcome. As a result, the sample used for machine learning analysis was slightly smaller than that used for logistic regression analysis. Homicide risk was removed entirely from these models because of large amounts of missing data. The sample used for analysis was divided into training and testing data in an 80-20 split. As the outcome variable for these models was binary, all models used accuracy, sensitivity (rate of true positives), and specificity (rate of true negatives) as measures of the models' success.

3 Results

3.1 Logistic Regression with Clustered Standard Errors

Logistic regressions with clustered standard errors were run three times: once on the full dataset, a second time on only the programs identified as low-supervision (REACH, Roger Sherman House, and the Sierra Center), and a third time on the high-supervision programs (Eddy Center and The January Center).

The first logistic regression was run on the full dataset and included suicide and homicide risk, program, race, all criminal thinking profile measures, and risk level of recidivism. Participants with a high risk level of recidivism were 59% less likely to successfully leave community justice programs than those with a low risk level ($z=-4.5$, $p < 0.001$), while those with a moderate risk level were 31% less likely to successfully leave community justice programs than those with a low risk level ($z=-2.6$, $p = 0.01$) after controlling for suicide and homicide risk, program, race, and all criminal thinking profile measures. Each point increase in justifying behavior increased participants' chances of success by 9% ($z=2.2$, $p = 0.02$) after controlling for risk level of recidivism, program, suicide and homicide risk, race, and all other criminal thinking profile measures. Participants at The January Center were 4 times as likely to succeed ($z=3.3$, $p < 0.01$) as those at the Eddy Center, while participants at REACH were 75% less likely to succeed ($z=-7.9$, $p < 0.001$), those at the Sierra Center were 36% less likely to succeed ($z=-0.44$, $p = 0.03$), and those at Roger Sherman house were 43% less likely to succeed ($z=-0.57$, $p = 0.01$) when participants at all three programs were compared to those at the Eddy Center after controlling for risk level of recidivism, suicide and homicide risk, all criminal thinking profile measures, and race. All variables are shown in Figure 1.

Given the presence of program as a highly statistically significant variable in predicting success, it was necessary to investigate it in more detail. Analysis of the relationship between risk level, program, and success aligned with the results of the logistic regression. This relationship is displayed in Figure 2. REACH stands out as program with an overall low success rate: only 25% of high-risk and 51% of low-risk participants were successful, and the program had an overall average success rate of 43%. On the other hand, participants at The January Center were much more successful, with a 100% success rate for high-risk participants, a 95% success rate for low-risk participants and an overall success rate of 93%. Overall average success rates were lower at the Sierra Center (62%) and Roger Sherman

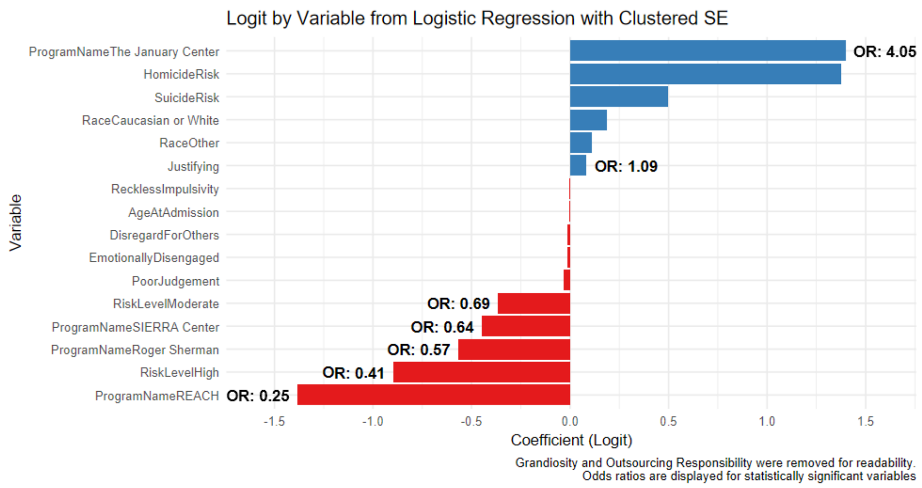

Figure 1: Log odds for variables from logistic regression with clustered standard errors

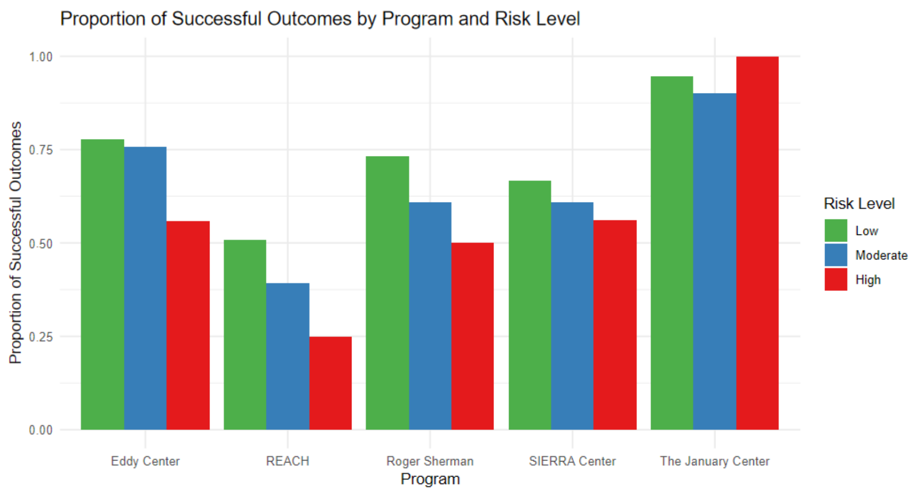

Figure 2: Success rates across all five programs, compared across risk levels.

House (61%) as well, with success rates at the Eddy Center (74%) higher than the rest of the programs, but falling below those of The January Center.

This disparity inspired further investigation into the programs with the worst success rates—REACH, Roger Sherman House, and the Sierra Center—which were also the programs with the lowest levels of supervision. A second logistic regression, including all the covariates of the first except program, was run on a subset of the data that only included these low-supervision programs.

Participants in the low-supervision programs with a high risk of recidivism were 41% less likely to succeed (z=-2.3, p = 0.02) and those with a moderate risk

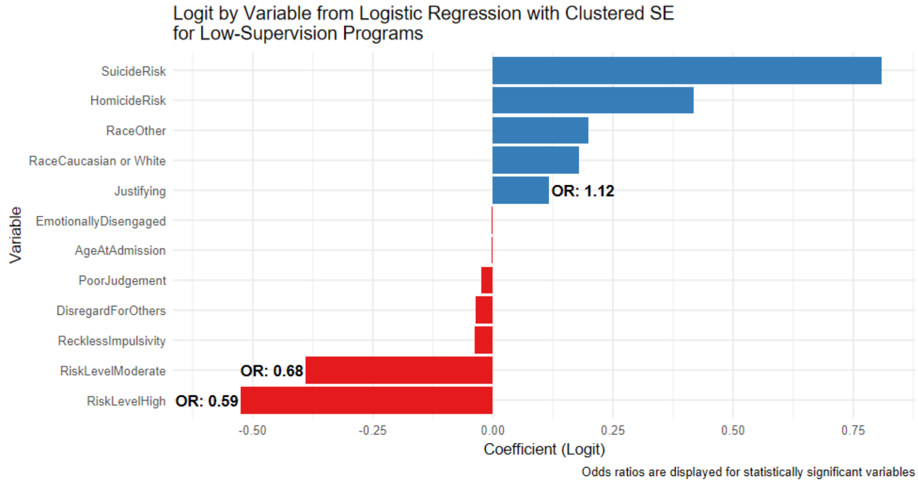

Figure 3: Log odds for variables from logistic regression with clustered standard errors, specifically for low-supervision programs.

of recidivism were 32% less likely to succeed (z=-2.5, p = 0.01) than those with a low risk of recidivism after controlling for suicide and homicide risk, race, and all criminal thinking profile measures. Each point increase in justifying behavior increased participants' chances of success by 12% (z=2.6, p = 0.01), after controlling for risk level of recidivism, suicide and homicide risk, all other criminal thinking profile measures, and race. All variables in this model are shown in Figure 3.

A third and final logistic regression with clustered standard errors was run on the high-supervision programs to identify if these programs, that were generally more successful, had different predictors of success than the low-supervision programs.

Participants in the high-supervision programs with a high risk of recidivism were 61% less likely to succeed (z=-0.95, p = 0.01)than those with a low risk of recidivism, after controlling for race, suicide and homicide risk, and all criminal thinking profile measures. Unlike in the previous logistic regressions, a moderate level of risk of recidivism is associated with a higher chance of success than a low level of risk of recidivism, but this result is not statistically significant. Justifying behavior was no longer statistically significant among participants at high-supervision programs, but participants identified as having homicide risk were

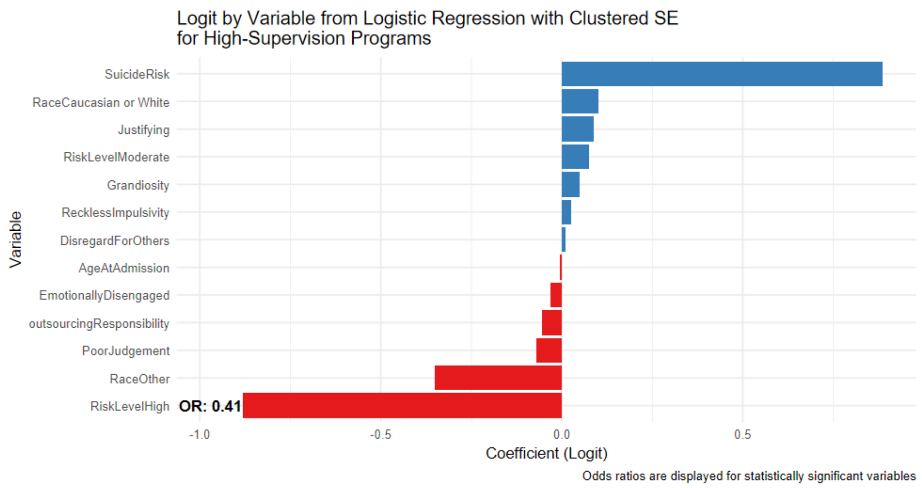

Figure 4: Log odds for variables from logistic regression with clustered standard errors for high-supervision programs.

4,386,400 times as likely to succeed than those with no homicide risk (z=15.29, p <0.001) after controlling for suicide risk, all criminal thinking profile measures, race, and risk of recidivism. However, this extremely high odds ratio is likely due to only nine participants having homicide risk in this subset and all nine of them have successful outcomes. Because the homicide risk result is most likely caused by small sample size, it will be ignored and high risk of recidivism will be considered to be the only statistically significant variable in this regression.

After removing homicide risk from analysis, participants in the high-supervision programs with a high risk of recidivism were 59% less likely to succeed (z=-0.88, p = 0.02) than those with a low risk of recidivism after controlling for race, suicide risk, and all criminal thinking profile measures, as shown in Figure 4. In this regression, high risk of recidivism is the only statistically significant predictor. Across all three regressions, risk of recidivism is a consistently significant and negative predictor of success—as a participant's risk of recidivism increases, their chances of success decrease, regardless of demographic factors, criminal thinking profile measures, suicide and homicide risk, and program.

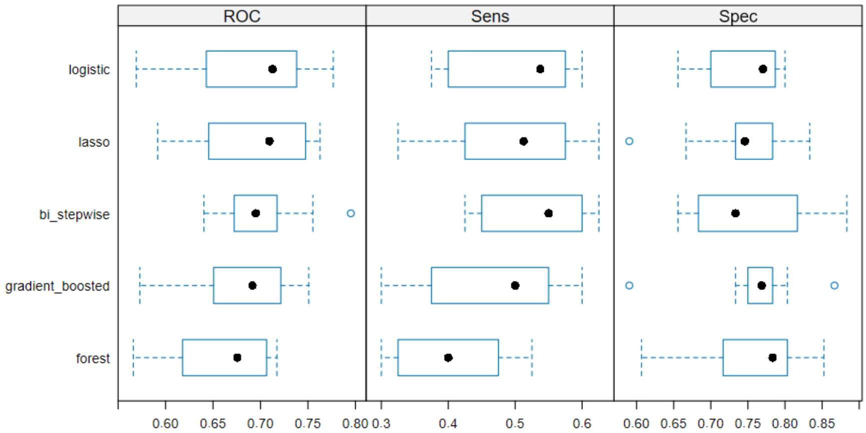

Figure 5: Boxplots of area under the ROC, sensitivity, and specificity for all models run on all programs.

3.2 Machine Learning

Lasso regression, bidirectional stepwise regression, random forest, gradient boosting, and logistic regression methods were run twice: once on the full sample of participants in all five programs, and a second time on participants only in the low-supervision programs (REACH, Sierra Center, and Roger Sherman House). These models were not run on the high-supervision programs alone becuase those programs alone did not provide a large enough sample.

The first set of machine learning models utilized criminal thinking profile variables, race, age at admission, program, risk level of recidivism, and suicide risk as predictors for outcomes from the program. After running all five models, the overall best model was determined to be the logistic regression model, based on results from the 10-fold cross-validated samples as shown in Figure 5. Any missing values were removed from the dataset using listwise deletion, which removed 85 participants (6% of the sample) from analysis.

However, as the goal of these feature selection models was to identify if models could effectively predict success rates for participants with fewer variables than were used in the original logistic regression, the lasso regression was chosen as the best model. The lasso regression was also identified as a better model than the

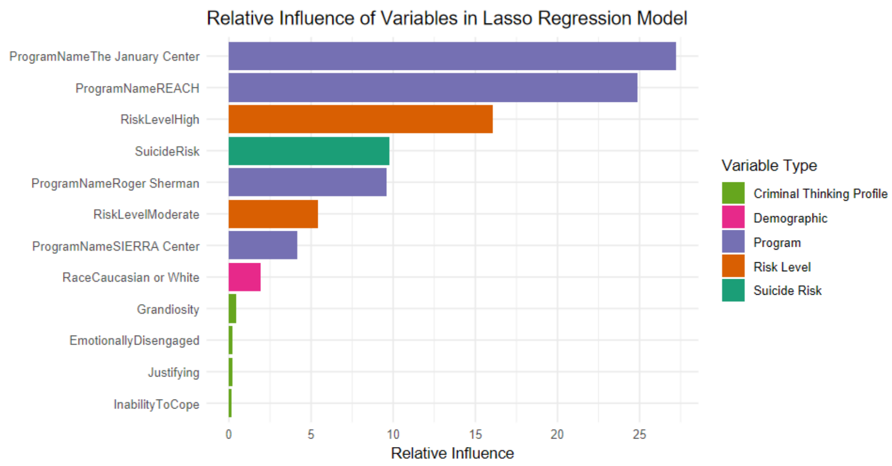

Figure 6: Variable importance for lasso regression model run on all programs.

logistic regression model because the lower bound of its accuracy in the 10-fold cross-validated samples was higher than that of the logistic regression model.

The final model utilized a λ value of 0.008, and identified 12 non-zero predictor variables, setting the coefficient for 7 of them to zero. The non-zero predictors for this regression are shown in Figure 6. The top five most important variables were whether the participant was at The January Center (OR=3.72), REACH (OR=0.30), Roger Sherman House (OR=0.63), if they had a high risk level of recidivism (OR=0.46), and if they were identified as having suicide risk (OR=1.60).

Criminal thinking profile variables of grandiosity (OR=1.02), emotional disengagement (OR=0.99), justifying behavior (OR=1.01), and an inability to cope (OR=0.99) were identified as non-zero coefficients, but had minimal importance in predicting success. Additionally, being white (OR=1.10), having a moderate risk level of recidivism (OR=0.77), and being at the Sierra center (OR=0.82) were identified as moderately important predictors of success. Within all of the non-zero predictor variables, being at The January Center, increases in justifying behavior, increases in grandiosity, and being white were positive predictors of success while being at REACH, Roger Sherman House or the Sierra Center, having a high or moderate risk level of recidivism, increases in emotional disengagement, and increases in an inability to cope were negative predictors of success.

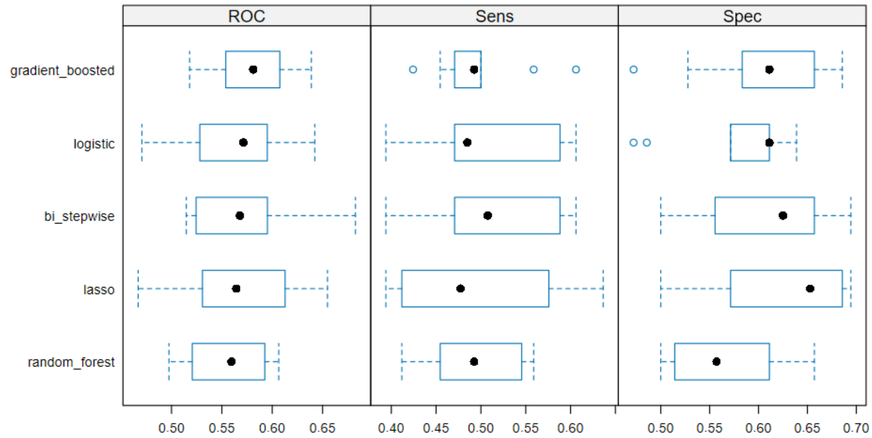

Figure 7: Boxplots of area under the ROC, sensitivity, and specificity for all models run on only low-supervision programs.

After using this model to predict successful outcomes for participants in the test data, it achieved a sensitivity of 78%, a specificity of 46%, and an overall accuracy of 62%. The model's sensitivity is unusually high, exceeding the maximum sensitivity of 63% on the training data, and its specificity is fairly low, smaller than the minimum specificity of 59% on the training data. Additionally, the model's accuracy is lower than anticipated, falling just above the minimum accuracy of 59% on the training data.

As with logistic regressions, these models were run on a subset of the data that included only participants in low-supervision programs. This set of models used the same variables as the previous ones. After running all five models, the overall best model was found to be the gradient-boosted regression, based on the results from the 10-fold cross-validated samples, as shown in Figure 7. Any missing values were removed from the sample using listwise deletion, which removed 47 participants (5% of the sample) from analysis.

The final model utilized 100 trees, each tree had a maximum depth of 2 splits, the learning rate multiplied by each tree before it was added to the overall model was 0.1, and a minimum of 10 observations were required per node in each tree. The top five most important variables in this model were age at admission, grandios-

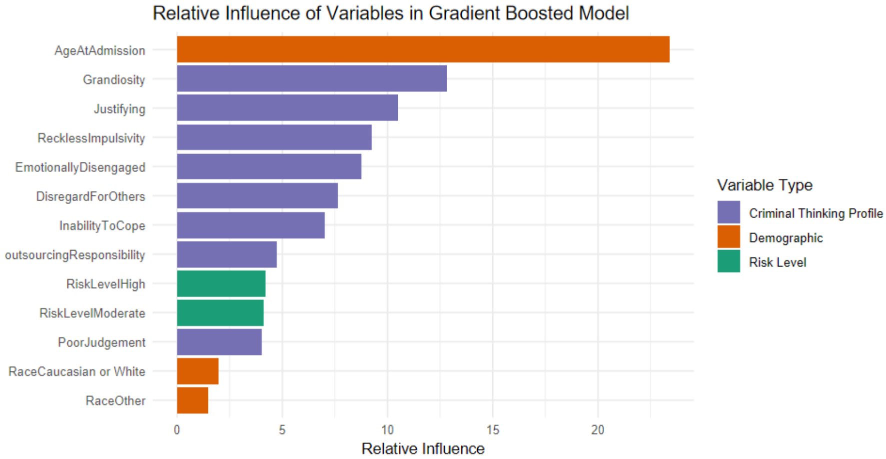

Figure 8: Variable importance for gradient boosted regression model run on low-supervision programs.

ity, justifying, reckless impulsivity, and being emotionally disengaged, as shown in Figure 8. Other important variables included disregard for others, inability to cope and outsourcing responsibitly. Measures of high and moderate risk levels of recidivism were also considered moderately important, alongside poor judgement. The least important variables in this moddel were if the participant was White or Caucasian or if they were some Other race.

Coefficients do not exist for the gradient boosted model because of how it is constructed, but it is possible to attempt to understand the average marginal effect of each of the independent variables through constructing a series of partial dependence plots. However, it is important to note that these variables are not forced to stick to a single trend—variables can change from being positive to negative depending on the range of values that they are given. All 11 variables and their marginal effects are shown in Figure 9.

There are some interesting trends in these graphs. Age, the most important variable, has an erratic trend. If a participant's age was below 30 or above 70, age at admission had a positive relationship with success, but within 30 to 70, it had a negative or no relationship with success. Risk level of recidivism shows an opposite trend to both the lasso regression run on all programs and all three logistic

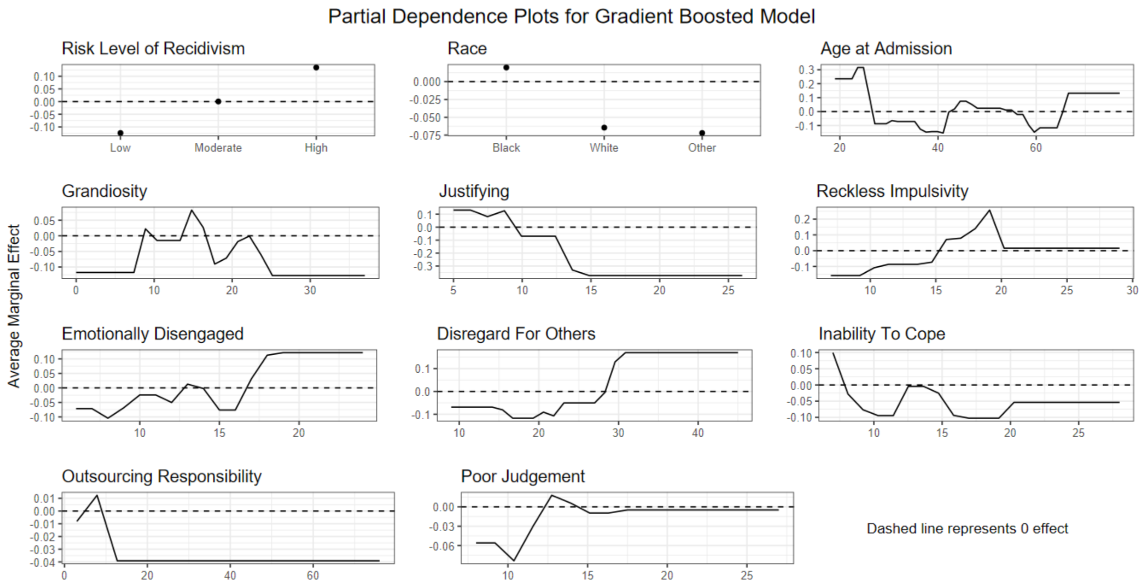

Figure 9: All 11 independent variables and their average marginal effects in the graident boosted regression model for low-supervision programs.

regressions: low risk of recidivism is negatively related to success, moderate risk has no relationship with success, and high risk is positive related to success. Being Black is positively related to success, while being White or some Other race are both negatively related to success.

The criminal thinking profile behaviors are grouped into a few different patterns. Justifying behavior, inability to cope, and outsourcing responsibility are all positively related to success at low values, but quickly become negatively related to success at higher values. Poor judgement and reckless impulsivity are negatively related to success at low values, positively related to success around the middle of their ranges, and have almost no relationship with success at higher values. Disregard for others and emotional disengagement are negatively related to success for low values, and positively related to success for high values. Grandiosity has a similar trend with age, being negatively related to success at the lowest and highest values in its range, and have a positive, neutral, or negative relationship with success for the values in the middle, jumping up and down in an unpredictable manner.

After using this model to predict successful outcomes for participants in the test data, it achieved a sensitivity of 60%, a specificity of 49%, and an overall accuracy of 54%. All three of these values fall into the ranges identified by the 10-fold cross-validated samples.

4 Discussion

Results from logistic regression models align with previous research, which has identified risk level as a negative predictor of successful reintegration D. Andrews et al. (2011); Fazel et al. (2024); Frisch-Scott and Nakamura (2022); Vitopoulos et al. (2012). A new finding in these models was the high significance of program, with The January Center having the highest level of success and REACH the lowest. The January Center's extremely high average success rate of 94% can be explained by its presence as one of the top facilities in the country for sex offenders. The program is an outlier both within this dataset and within the United States as a whole.

However, despite The January Center's status as a particularly successful program, there remains a noticeable difference between the high-supervision (The January Center and the Eddy Center) and low-supervision programs (REACH, Roger Sherman House, and the Sierra Center) in this dataset. Low-supervision programs achieve less success overall than high-supervision programs. However, risk level of recidivism remains a significant predictor of success rates across all programs, even when isolating high- and low-supervision programs. As this paper is the first to analyze this dataset at a program level, there is no literature to compare these findings against.

These results are consistent with lasso regression results run on all five programs, reaffirming the strength of risk level of recidivism as a predictor of successful outcomes for participants in The Connection's programs. Given that the program a participant is in is a significant factor in predicting success rates, The Connection should carefully evaluate participant's risk levels of recidivism alongside their progress before transferring them to programs with lower levels of recidivism. Participants with high risk levels of recidivism are especially likely to be not successful in the lower-supervision programs and should be carefully monitored and supported to ensure higher levels of success.

Another interesting and unexpected result in the logistic regressions run on all programs and just on low-supervision programs was the statistically significant positive relationship between justifying behavior and success. Justifying behavior has a positive relationship with success in the lasso regression run on all programs and for low values in the gradient-boosted regression run on low-supervision programs. These results are not aligned with the literature, which finds that those with higher levels of criminal thinking behavior experience lower levels of success in community justice and treatment programs (Best et al., 2009; Garner et al., 2007; Mitchell et al., 2013)

While it is difficult to explain why an increase in justifying behavior would increase chances of successfully leaving programs run by The Connection, it is possibly related to the fact that the sample in this dataset only includes people who have already committed a crime. Given that these measures are related to criminal behavior, and all of these individuals are confirmed to have participated in criminal behavior, it is possible that this measure and all other criminal thinking profile measures are not particularly useful within this context.

While these are promising results, it is important to note that there are some limitations within this project. All machine learning models utilized in this project—both those for all programs and those for just low-supervision programs—had smaller samples than the logistic regression models. Many variables found to be significantly related to recidivism in the literature, such as mental health problems (Houser et al., 2019; Ryan et al., 2013; Sadeh & McNiel, 2015), unemployment (Gill & Wilson, 2017; Harding et al., 2018; Kolbeck et al., 2022), low levels of education, and substance use (Gill & Wilson, 2017) were either not present in the dataset or had too many missing values to be included, which limited the efficacy of feature selection machine learning models. Looking too closely at specific programs reduced the efficacy of these models, likely because of the lack of the aforementioned variables and smaller than ideal sample sizes.

An additional limitation that was responsible for many of the high rates of missing data was the fact that this dataset was collected for reporting purposes rather than research purposes. Participants are not required to answer demographic questions. Additionally, not all participants were provided with the suicide and homicide risk questionnaires as the suicide risk questionnaire was only put into practice recently. The goal of the data collection also means that many important variables, such as if participants are able to successfully re-integrate with their communities and data on re-arrests that happen outside the program, are not included in this dataset.

5 Conclusion

This capstone established a significant relationship between risk level of recidivism and success rates in programs run by The Connection through both lasso regression and three kinds of logistic regressions with clustered standard errors. The program participants were in was also found to be extremely significant, with REACH, the Sierra Center, and Roger Sherman House having a negative relationship with success and The January Center having a positive relationship with success, when comparing participants in these programs to those in the Eddy Center. Justifying behavior was the only consistently significant criminal thinking profile measure and was positively related to successful outcomes.

Future research into this topic should explore other factors that are key determinants of successful outcomes, including education level, ethnicity, gender, unemployment, mental health, and substance abuse. Any new data collected by The Connection should be reanalyzed within these models to understand how other factors relate to successful outcomes at these community justice programs.

Additionally, future projects could go beyond the scope of this capstone to identify how the factors of risk level of recidivism, race, age at admission, suicide and homicide risk, criminal thinking profile measures, and program relate to successful reintegration for participants after they have successfully left these programs. Going beyond the scope of this project to understand future outcomes for these participants could help further support The Connection's goal of ensuring long-term success for participants in their programs.

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