Utilization of machine learning for identifying causal mechanisms underlying children's involvement with the criminal justice system

Jonah Shi

Advisor 1: Sisi Ma Institute for Health Informatics, University of Minnesota, Minneapolis, MN, USA

Advisor 2: Lupo Geronazzo University Department of Psychiatry and New York State Psychiatric Institute, New York, NY, USA

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Contents

1 Abstract

Background Children of parents involved with the criminal justice system involvement (CJSI) have higher rates of CJSI (e.g., being arrested) than the general population. However, research on children of parents involved with CJSI is scarce, and little is known about the factors involved in the "transmission" of risk for CJSI from parents to children.

Methods In this study, data was gathered from parents and children involved with the CJSI. We aim to identify causal factors that influence children's involvement in criminal justice system. We used Greedy Recursive Sparse Projection in Fast Causal Inference (GRaSP-Fci) algorithm for causal structure discovery, generating a causal graph to describe the causal relationships among the measured variables. We used bootstrapping to assess stability of the identified causal relationships. Finally, we used Lavvan to estimate quantitative causal relationships and conducted simulated intervention on one of the variables to test how will this impact the other variables.

Results We identified previously described and novel causal relationships with important implications. Specifically, the delinquent behaviors for juveniles at follow-up in one year compared with the baseline does not decrease following arrest at baseline, instead, juvenile CJSI stands as a negative turning point during adolescence, causally linked to increased severity of conduct disorder, increased delinquent behavior, and a higher chance of being arrested at an older age. The simulated interventions revealed that intervention for conduct disorder symptoms is an important potential intervention target for children with high risks of involvement with CJSI.

Conclusions Our analysis revealed important causal factors for children's involvement with the CJSI, suggesting alternative approaches to approach juvenile delinquency.

2 Introduction

More people are incarcerated in the United States than in any other country in the world [3]. Furthermore, even though the trend has been decreasing over the years, millions of people are arrested each year and held in city or county jails (more than 7 million in 2022) (FBI, 2023). Children exposed to parental criminal justice system involvement may exhibit several difficulties, such as externalizing behaviors (i.e., antisocial behavior, delinquency, CJSI), internalizing behaviors (i.e., depression, anxiety), and substance use [1].

The evidence summarized above presents a compelling case for studying the relationship between parental CJSI and their children's adverse outcomes, including possible future delinquent behavior and arrest. However, although much research has focused on adults who have been incarcerated, the impact of mass incarceration on children, indirectly affected by the CJSI of a family member, has been largely overlooked by researchers and policymakers and has not been systematically assessed [1][11]. CJSI effects on children are most generally neglected in academic research, prison statistics, public policy, and the media [12][1]. Furthermore, most research on the effects of parental CJSI focuses on the impact of lengthy terms of incarceration in prison. However, this population represents only a small fraction of parents involved with the CJSI; only a small minority of those arrested and temporarily jailed are sentenced to additional jail time or prison.

In response to this lack of rigorous research, a study (see Methods section) on the impact on children of maternal and paternal CJSI conducted at Columbia University (PI: C. Hoven) aimed to overcome the aforementioned methodological limitations and provide generalizable findings [1].

First, we built and validated accurate causal models of juvenile CJSI (qualitative causal discovery). We focused on examining the causal relationships between parental CJSI and five main sets of children's outcomes: psychiatric disorders, delinquent behavior, personality disorders, functional impairment, and CJSI. To distinguish correlative and causative relationships, we inferred the causal structure of juvenile CJSI with a state-of-the-art, novel machine-learning causal discovery analysis algorithm (GRaSP-FCI) that can distinguish causation from correlation due to confounding variables. To our knowledge, there are no causal models of juvenile CJSI. Discovering causal factors involved in children's CJSI is essential to identify candidate intervention targets to reduce the risk of CJSI during childhood and adolescence. Consequently, the second aim was to identify candidate intervention targets and estimate their causal effect on juvenile CJSI (quantitative causal effect estimation). The causal relationships modeled in Aim 1 were translated into practical implementations by identifying likely manipulatable causal factors (i.e., amenable to intervention) and estimating the causal effect on juvenile CJSI resulting from simulated interventions.

3 Method

3.1 Data acquisition and processing

Data for this study were drawn from a two-wave NIDA-funded study (R01DA023733 and R01DA024029, PI: Hoven) of parents involved with the criminal justice system (CJS) and their children (ages 9-15; n=418); a control sample (no history of parental CJS involvement since the birth of the child; n=344), matched to the index child by age (minus or plus 1 year), gender and geographic proximity (within a radius of 0.5 miles) was also recruited [7]. Thus, N=762 children and their parents were assessed. Our analytical sample comprised N=601 children with complete data on all the variables examined. The sample is composed predominately of minority (Black and Hispanic) children and adolescents from the low-SES, high-crime areas of the South Bronx, one of the five boroughs that make up New York City. CJSI parents were recruited from the Bronx Criminal Court. The study was facilitated through a contractual collaboration with the Bronx Defenders, an organization providing legal representation to those arrested and charged with crimes in the Bronx.

3.1.1 Survey method

A critically important feature of this study is the representativeness of mothers and fathers with children ages 9 through 15 arraigned in the Bronx Criminal Court. Parents were identified at arraignment, where all individuals arrested within the previous 24 to 72 hours are processed, regardless of the nature of the crime. The sample of parents involved with the CJSI, whose case had been assigned to The Bronx Defenders, were brought from lock-up to arraignment, where they were initially recruited just before a judge's case disposition. During the S&J Study, in-home, face-to-face interviews were conducted with both parents and children. The follow-up interview took place 12 months after baseline. All study participants received financial incentives for their participation in the Study. The Columbia University-New York State Psychiatric Institute's IRB approved the study.

3.1.2 Data processing and variable construction

There are 62 variables examined in the study measured during the baseline and follow-up interviews. These variables capture the characteristics of the children and their parents in the following five board categories: psychiatric disorders, delinquent behavior, personality disorders, functional impairment, and CJSI.

In the current study data from 762 participants were included. Participants with any missing data were excluded from the analysis.

3.2 Statistical analysis

3.2.1 Analysis design

The primary goal is to identify the factors that influence children's involvement with the criminal justice system and to identify effective interventions that reduce children's involvement. To achieve this goal, we first used causal structure discovery methods to estimate the causal relationships among the variables in this dataset and assessed the stability of the discovered causal relationships with bootstrapping. We then estimated the causal effects associated with the discovered causal relationships using structural equation modeling. We further conducted a simulated experiment to estimate the effect of reducing the number of symptoms of Conduct Disorder on other variables.

3.2.2 Identification of causal structure

We used GRaSP-FCI, Greedy Relaxations of Sparse Projection in Fast Causal Inference, to estimate the causal structure underlying the data. GRaSP-FCI combines the GRaSP algorithm and the FCI algorithm. The GRaSP portion of GRaSP-FCI identifies the causal skeleton (i.e. which variables are causally directly connected with which other variables, regardless of causal direction), and orientations of causal relationships up to statistical equivalence. GRaSP is designed to efficiently handle high-dimensional data especially effective when the causal graph underlying the data is dense[8]. The FCI portion of GRaSP-FCI is applied after GRaSP to identify the potential presence of hidden variables (i.e. unmeasured confounders). The ability to identify hidden variables is important since their presence affects causal effect estimation.

The final causal graph estimated by the GRaSP-FCI is represented as a partial ancestral graph (PAG), which denotes all statistically equivalent Maximal ancestral graphs (MAGs). The edge types in a PAG are shown in Figure 1.

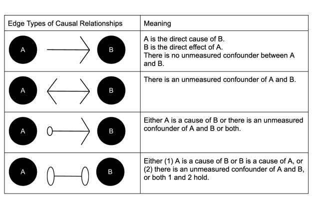

Figure 1: Four types of causal relationships

We used GRaSP-FCI implemented in Causal-Cmd version 1.11.1 [4].

3.2.3 Assessing the stability of the estimated causal graph

To assess the stability of the discovered causal graph, we used the bootstrap resampling technique. 100 bootstrap datasets (sampling with replacement) were generated. GRaSP-FCI was applied to each bootstrap sample to derive a causal graph. The frequency (%) of the discovery of a specific causal relationship was used to estimate its stability.

3.2.4 Causal effect estimation

Given the identified causal relationships, we then quantified their causal effects. The causal effect of Y on X is defined as the amount of change in variable X when variable Y is changed by one unit, while holding the other variables constant. The standardized causal effect is defined as the change in variable X expressed as units of standard deviation when variable Y is changed by one unit, while holding the other variables constant. To estimate the causal effects, we fit a structural equation model based on the estimated causal structure. The β coefficients and standardized β coefficients of the structural equation model correspond to the estimated causal effects and estimated standardized causal effects.

We used the Lavaan package in R to fit the structure equation model. [5].

We used Standardized Root Mean Square Residual (SRMR) and Comparative Fit Index (CFI) [6] to assess the goodness of fit of the structural equation model to the data.

3.2.5 Simulated interventions

We answered the question "How much change would be observed in other variables if we changed the number of symptoms of Conduct Disorder at baseline ($Y0\_CD$) in children with at least 1 symptom of conduct disorder? We conducted the analysis to simulate this intervention based on the Structural equation model estimated above.

$Y0\_CD$ can have a causal impact on other variables X in two ways: a direct causal influence, where $Y0\_CD$ is influencing variable X through a direct causal edge; and, indirect causal influence, where $Y0\_CD$ is influencing X through a directed path involving other variables creating a chain of influence that ultimately impacts X. For a particular variable X, $Y0\_CD$ can influence it in one of the above ways, or both. The total influence of $Y0\_CD$ on other variables in the dataset was estimated in the simulated intervention.

The total influence of $Y0\_CD$ on variable X is the sum of the influence across all directed paths (direct and indirect) from $Y0\_CD$ to X. To compute the influence of one single path, the change in $Y0\_CD$ is multiplied by all the β coefficients of the edges that are part of the path sequentially. An example is shown in [Fig. 2]. For direct causal relationships, such as the first graph in [Fig. 2],we have $Y0\_CD$ causing $Y1\_CD$, with the linear relationship $Y1\_CD = 0.44 * Y0\_CD + b1$. When $Y0\_CD$ decreases by 75 percent, the average of $Y0\_CD$ decreases by 1.12, and $Y1\_CD$ will decrease by $1.12 * 0.44 = 0.49$. For indirect causal relationships, we illustrate with the second graph in [Fig. 2], with $Y0\_CD$ causing $Y1\_MUD$ through $Y1\_ARREST$ and $Y1\_CD$. For the first causal path, as a result of decreasing $Y0\_CD$ by 75%, $Y1\_ARREST$ will decrease by $1.12 * 0.081 = 0.091$, which will finally result in a decrease of $Y1\_MUD$ by $1.12 * 0.081 * 0.45 = 0.041$. In the other path, as a result of decreasing $Y0\_CD$ by 75%, $Y1\_CD$ will decrease by $1.12 * 0.44 = 0.49$, which finally results in the decrease of $Y1\_MUD$ by $1.12 * 0.44 * 0.10 = 0.049$. Adding the causal effect of the two paths together, it becomes $0.041 + 0.049 = 0.09$.

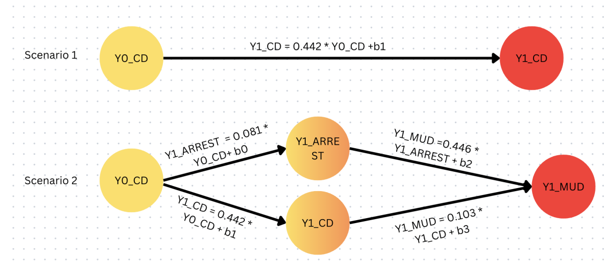

Figure 2: Examples of simulated interventions

4 Result

4.1 Sample characteristics

After excluding the missing data, data from N=762 children and their parent(s) were included in this study. A total number of 62 variables were assessed. These variables fall into three categories: (1) constitutional variables capturing the children's age, gender, and their parents' prior experience with the criminal justice system. (2) baseline variables capturing the children's behavior, psychological status, and their interaction with the criminal justice system during the baseline of the study. (3) Year one variables capturing the children's behavior, psychological status, and their interaction with the criminal justice system during the second year of the study. Key variables were listed in Table 1.

In this dataset, the average age of the children is 12.21. 48.6% of them are male. 29.8% of them experienced maternal criminal justice system involvement, and 24.3% of them paternal criminal justice system involvement. The children's arrest rate is 3.8% at baseline and 9.2% at year one.

4.2 Identification of causal structures

Following the application of the GRaSP-FCI algorithm via the Causal-Cmd tool, a comprehensive causal graph was generated, comprising 62 variables and 136 edges. Among these edges, 121 were identified as direct causal relationships, while 8 were identified as confounded relationships, and 7 were deemed

Categorical Variables with only 0 and 1 Average of Being True	Baseline Avg	
maternal lifetime involvement with the criminal justice system	0.298	
paternal lifetime involvement with the criminal justice system	0.243	
child's gender; 0=female, 1=male	0.486	
child's arrest at baseline	0.038	
child's arrest at year one	0.092	
Numerical Variables	**Baseline Avg**	**1 Year Avg**
child's age	12.21	
Cognitive and perceptual dysregulation factor score	6.16	6.27
Impulsivity factor score	6.59	11.87
Odd/unusual beliefs and experiences factor score	6.44	6.4
Hostility factor score	6.57	4.73
Withdrawal/detachment factor score	3.31	3.22

Table 1: Study sample characteristics and variable descriptive statistics

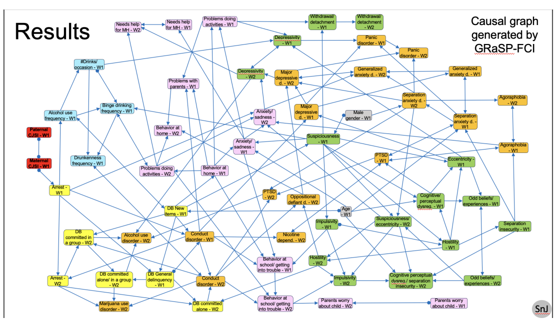

Figure 3: Estimated causal relationships among variables related to children's involvement with the criminal justice system

potentially confounded [Fig. 3]. Several important causal relationships between the child's conduct disorder at baseline and the child's behavioral and psychological characteristics, as well as the child's involvement with the criminal justice system, were identified. We further explore these relationships in the following subsections.

4.3 Stability of the identified causal relationships

To assess the stability of the identified causal relationships, we conducted bootstrap resampling where the causal discovery analysis was applied to 100 bootstrap samples of the datasets. Out of the 136 edges identified by applying GRaSP-FCI to the full data, 34 edges were very stable (appeared in $> 90\%$ of the bootstrap samples), 69 edges were stable (appeared in $> 75\%$ of the bootstrap samples), 56 edges had intermediate stability (appeared in 75% 50% of the bootstrap samples), the rest of the edges has low stability (appeared in $< 50\%$ of the bootstrap samples).

The most stable causal relationships are listed in table 2, along with the percentage of how often they appear in the bootstrap analysis. The only direct cause of juvenile arrest at baseline is the variable measuring the number of different types of delinquent behaviors with a bootstrap stability of 56%. Moreover, two factors impact the juvenile arrest at the follow-up. Juvenile arrest at baseline causes the juvenile arrest at the follow-up, with a bootstrap stability of 70%. Conduct Disorder also causes juvenile arrest at follow-up with a bootstrap stability of 56%. The data also shows that juvenile CJSI can also have a negative impact since juvenile arrest at follow-up leads to juveniles having delinquent behaviors in a group setting with 89 % bootstrap stability, and delinquent behaviors alone with 73 % bootstrap stability.

4.4 Causal effect estimation

To estimate the causal effect among the variables in this dataset, we fitted a structural equation model. This model consists of 117 linear regression equations representing direct causal relationships, 127 covariance, and 64 Variance terms. We show the most important causal relationships and their standardized effect sizes in [Fig. 4].

Standardized effect size (ES) in [Fig. 4]. represents the amount of change observed in another variable (the effect). When one variable (the cause) is changed by one standard deviation. For example, when $Y0_CD$ is changed by one standard deviation, $Y0_MDD$ is changed by 0.554.

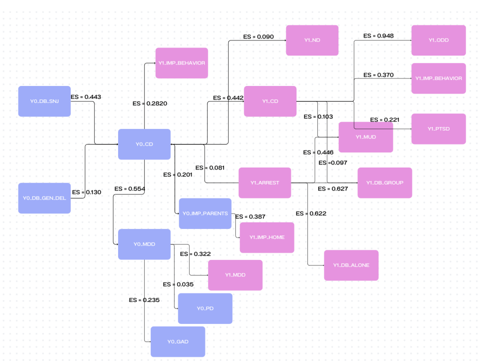

Figure 4: Important Causal Relationships within the Dataset

4.5 Simulated interventions

As indicated in the discovered causal graph, a child's severity of conduct disorder is a key factor that can impact many downstream behavior and psychological characteristics and their involvement with the criminal justice system. Also, interventions exist to improve conduct disorder. Therefore, we estimate the effect of decreasing conduct disorder $Y0\_CD$ on the child's behavior and psychological characteristics and their involvement with the criminal justice system. Specifically, we simulated decreasing the $Y0\_CD$ by 75 percent among those who have the disease disorder.

We list the effect of decreasing conduct disorder at baseline on other variables in [Fig. 5]. We only listed variables with changes larger than 20 percent [Fig. 5].

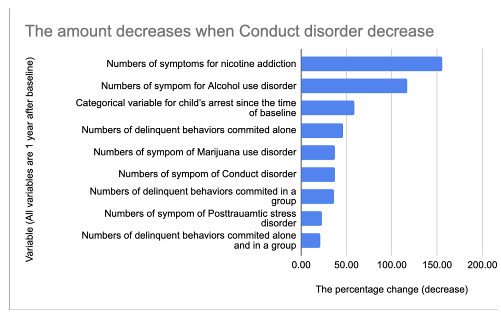

Figure 5: The actual decreases when Conduct disorder decreases

5 Discussion

The causal paths from arrest at baseline to conduct disorder and a higher number of delinquent behaviors at baseline and to arrest at follow-up, which is, in turn, causally linked to other variables measuring delinquent behaviors at follow-up, are particularly interesting. While some studies find that CJSI may deter future offending, another body of research indicates that CJSI can increase delinquency among youth [10]. The modeled causal relationships support prior research noting the adverse effects of punitive responses on delinquency and extend it to a representative urban low-income minority sample of children of parents involved with CJSI. Given the

Source	Target	Percentage	Dataset edge type
Separation anxiety disorder at baseline	Separation anxiety disorder a year after	1	$-->$
Major depressive disorder at baseline	Major depressive disorder a year after	1	$<->$
Suspiciousness/Eccentricity factor score a year after	Impulsivity factor score a year after	1	$-->$
Impulsivity factor score a year after	Sum of personality disorder a year after	1	$-->$
Behavior at home factor score a year after	Problems with doing activities factor score a year after	1	$-->$
Generalized anxiety disorder a year after	Major depressive disorder a year after	1	$-->$
Conduct disorder a year after	Oppositional defiant disorder a year after	1	$-->$
Juvenile arrested 1 year after	Delinquent behaviors committed in a group	0.87	$-->$
Juvenile arrested 1 year after	Delinquent behaviors committed alone and in a group	0.73	$-->$
Juvenile arrested at baseline	Juvenile arrested 1 year after	0.70	$-->$
delinquency disorder factor score	Juvenile arrested at baseline	0.56	$-->$
Conduct disorder at baseline	Juvenile arrested 1 year after	0.56	$-->$

Table 2: Causal relationships with highest stability or clinical interests and in Bootstrap

impact that formal sanctions, such as arrest, can have on delinquency, several implications exist. Developmentally, these findings indicate that juvenile CJSI can stand as a negative turning point during adolescence, causally linked to increased severity of conduct disorder, increased delinquent behavior, and a higher chance of being arrested at an older age.

According to labeling theory, two distinct mechanisms (secondary deviance and secondary sanctioning) could drive continued offending. First, a formal record of arrest can be internalized as a negative label that identifies the juvenile as a delinquent, contributing to the formation of a deviant self-concept that promotes "secondary deviance" (a sociological concept that describes how society's reaction to it can amplify someone's deviant behavior) and, in turn, increases levels of subsequent offending [9]. Second, the impact of arrest at an earlier age might lead to "secondary sanctioning"; secondary sanctioning refers to the social and societal consequences, outside of the justice system, a young person might face after an arrest, such as social stigma, reduced opportunities for employment, education, and housing, disruptions of prosocial bonds and reduction of social opportunities. Cumulatively, the two processes of secondary deviance and secondary sanctioning can dramatically reshape an individual's life course and lead to an increased likelihood of future arrest and further offending [10].

These results suggest that agencies' approach to juvenile delinquency should be reconsidered to include alternatives to formal sanctions. Based on this analysis, the continued use of punitive responses alone to curb juvenile delinquency will likely produce adverse effects in the form of ongoing and heightened forms of offending. These findings reflect the literature above linking arrest to delinquent behavior, which questions the efficacy of punitive sanctions to reduce recidivism, especially among juvenile offenders. Therefore, strategies should be implemented to minimize the adverse effects of arrest and identify and address risk factors associated with future delinquency. Drawing from evaluation-based research, potential strategies to address a range of offending include providing police with alternatives to arrest, providing social, cognitive, and skill-building programs to "at-risk youth," building prosocial bonds after police contact, evaluating the risks, needs, and responsively of youth, implementing corrective school-based, and employing family-based interventions [10]. Moreover, we can't just look at this causal relationship, there maybe some other confounding variables may also cause this issue. In the future, we will conduct more studies to judge the accuracy of our research and experiments.

6 Limitations and conclusion

Our study has several limitations. First, based on the survey, some of the questions are connected. It is hard to distinguish them, and because of that, it will be hard to know how one variable specifically changes the other, instead of the related variable that will be changed. In the future, using methods to avoid this indirect change will increase the accuracy of the research. Second, while doing the Lavaan algorithm, some of the data will decrease too much to a negative value, which would not have any real-world meanings. Also, the calculation for identifying the causal path of Lavaan is different from identifying the GRaSP-FCI, there is a difference in how many causal paths are there in the dataset. Future studies can improve in this area and find out the reason why this happens.

Furthermore, the bootstrap method used in our analysis also cannot verify whether all confounding variables have been captured. Confounding occurs when a risk factor is associated with both the comparison variable and the outcome of interest. The method for controlling confounders in observational studies is adjusting for their effects. However, the findings from such studies are subject to bias if researchers do not adequately adjust for confounding variables. Even if I adjust for the confounding variables, it cannot be verified that all confounding variables have been captured, as there is no way of accounting for the effects of potential unknown confounders. Therefore, the conclusions drawn from this observational studies needs further research [2].

To our knowledge, this will be the first study to model the direct causal pathway between juvenile CJSI's psychiatric disorders, delinquent behavior, personality disorders, functional impairment, and CJSI itself. All of these findings have high clinical importance for improving the usage of the CJSI and making the agencies reconsider the approach to juvenile delinquency, including alternatives to formal sanctions.

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