Intensive Outpatient Clinic Criminal Justice Impact Evaluation

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Executive Summary

The Intensive Outpatient Clinic (IOC) at the University of Utah provides comprehensive healthcare services to high-need Medicaid beneficiaries who frequently utilize emergency medical services or experience multiple chronic health conditions. This executive summary presents key findings and implications from an evaluation of the clinic's impact on criminal justice outcomes.

Study Overview and Methodology

This evaluation examined whether IOC participation influences criminal justice metrics. The study compared 103 IOC participants to a matched control group of Medicaid beneficiaries not enrolled in the IOC. Data sources included IOC records, Salt Lake County Jail records, Medicaid records, and public data on COVID-19 case severity.

The methodology involved:

- *Data Integration*: The initial phase combined Medicaid claims data (April 2020-March 2024), Salt Lake County Jail booking data (2009-present), and IOC program data through probabilistic record linkage.
- *Principal Component Analysis (PCA)*: PCA reduced the dimensionality of Medicaid variables while preserving approximately 70% of variance in just three components that captured: 1) healthcare system engagement, 2) chronic disease management patterns, and 3) cost efficiency of healthcare utilization.
- *Covariate Balancing Propensity Score (CBPS)*: CBPS was used to create comparable treatment and control groups by simultaneously optimizing treatment prediction and covariate balance. This method achieved excellent balance across all covariates with all standardized mean differences well below 0.10, and the largest at 0.04.
- *Model Selection*: The model selection process compared multiple distributional forms (Negative Binomial, Zero-inflated Negative Binomial, Hurdle Negative Binomial, Zero-inflated Hurdle Negative Binomial, and Zero-inflated Beta Binomial) for outcome variables using Akaike Information Criterion (AIC) to select the best-fitting model for each.
- *Diagnostics*: Model validation included QQ plots, zero-inflation tests, dispersion tests, and outlier identification to ensure appropriate model fit.

Key Findings

Although positive findings below are tempered somewhat by the low base rates of criminal justice contact (see full report), the evaluation revealed substantial reductions in criminal justice involvement among IOC patients (predicted values are extrapolated to the current IOC population size of 307).

- **The treatment group had 71% fewer arrests than the control group** (predicted 41 vs. 138, statistically significant, $p < 0.001$).
- **The treatment group had 50% fewer days in jail than the control group** (predicted 2,664 vs. 5,338, marginally significant, $p = 0.074$)
- **The treatment group had a 73% reduction in maximum crime severity relative to the control group** (predicted 1 [Infraction] vs. 2 [class C misdemeanor], statistically significant, p < 0.001)

Key Limitations

Several limitations should be considered when interpreting results:

- *Short Observation Period*: Owing to limitations of historical Medicaid data, the follow-up period was relatively short for the criminal justice outcomes. It is impossible to know whether the observed effect would be maintained, reduced, or augmented over a longer follow-up period.
- *Limited Sample*: The analysis included only 103 of 307 IOC participants due to Medicaid data constraints, which might raise questions about generalizability to the full IOC population.
- *Pandemic Effects*: While the study included a variable accounting for COVID-19 case rates, the pandemic dramatically affected both healthcare utilization and criminal justice operations in ways that may not have been fully captured.
- *Unobserved Confounding*: Despite sophisticated matching methods, the non-randomized design cannot eliminate potential selection bias from unmeasured factors that influence both treatment participation and outcomes. Here, unmeasured confounder refer to hidden factors the study did not capture that might alter a person's likelihood to receive treatment at the IOC and their eventual outcomes. For example, if more motivated patients are more likely to enroll in the IOC, their better outcomes could stem from their unmeasured motivation rather than the treatment itself.
- *Treatment Heterogeneity*: Because researchers did not receive IOC care records from University of Utah Health Plans (UUHP), the study design could not capture variations in IOC implementation or dosage that could affect outcomes.
- *Limited Criminal Justice Metrics*: Reliance solely on jail data may miss other important criminal justice predictors as well as outcomes such as Failure to Appear (FTA) for court appearances, court convictions, or probation/parole violations.

Methodological Strengths

Limitations not withstanding, the study utilized several strong methodological and statistical techniques that enhance confidence in its findings:

1. The CBPS methodology achieved excellent balance across all covariates, with all standardized mean differences well below 0.10. This indicates that, on observed/known confounding variables, the weighted control and treatment groups were similar, strengthening the assertion that differences between groups were meaningful.

2. The large effect sizes (particularly the 70.9% reduction in arrests) would require very strong unobserved confounders to be completely negate the findings, which increases confidence in the benefits of the intervention.

3. Consistency of positive outcomes across three related but distinct criminal justice outcomes strengthens confidence in the findings.

Summary

While acknowledging the inherent limitations of observational studies and quasi-experimental approaches, the large effect sizes, consistency across outcomes, and practical significance of the findings, all serve as compelling reasons to further examine IOC's effectiveness at reducing criminal justice contact. This could be expanded to include Utah Court and Bureau of Criminal Identification (BCI) data to test the robustness of criminal justice findings, but to also consider additional confounders (i.e., unmeasured variables that could affect findings).

1 Background and Purpose

1.1 IOC Background

The Intensive Outpatient Clinic (IOC) at the University of Utah aims to provide comprehensive healthcare services to high-need Medicaid beneficiaries who frequently utilize emergency medical services or experience multiple chronic health conditions. The clinic provides intensive, coordinated care and seeks to improve health outcomes, reduce unnecessary emergency department visits, and enhance overall quality of life for patients. Additional program information can be found here.

The clinic's potential impact on criminal justice outcomes stems from its focus on addressing underlying factors that contribute to justice system involvement. Some high-utilizers of emergency medical services also experience substance use disorders, serious mental illness, housing instability, and other social determinants of health that increase their risk of criminal justice contact. This evaluation specifically examines whether IOC participation affects criminal justice metrics such as jail bookings, length of jail stays, and offense severity, providing insights into the clinic's broader societal benefits beyond healthcare utilization.

1.2 Study Purpose

This document provides a relatively succinct summary of the methodology for evaluating IOC at the University of Utah as it relates to potential effects on criminal justice outcomes. The evaluation integrates data from three key sources to enable statistical analysis of the clinic's potential impact. These data sources include:

- IOC patient list containing 307 individuals with Medicaid identification numbers and clinic start dates.
- Medicaid claims data spanning from April 1, 2020, to March 31, 2024, including eligibility records, medical claims (diagnoses and procedures), and pharmacy claims.
- Salt Lake County (SLC) Jail booking data spanning from 2009 to present with booking/release dates, charge information, and personal identifiers.

Additionally, this document outlines the approach to creating comparable treatment and control groups, recoding healthcare and jail data into analytically meaningful variables, and implementing probabilistic record linkage to identify and match individuals across data systems. This process establishes the foundation for subsequent analysis using Covariate Balancing Propensity Score (CBPS) methods.

1.3 Brief Literature Review

The ultimate goal of this study was to successfully match IOC patients with a similar comparison group in order to test the efficacy of the clinic with respect to criminal justice outcomes. The propensity score matching framework dictates that predictor variables should be selected based on their relationship to outcomes rather than treatment alone:

- Variables related to the outcome (but not exposure) should always be included as they increase precision without increasing bias.
- Variables related to the exposure (IOC) but not the outcome should generally be excluded.
- Including variables strongly related to exposure but only weakly related to outcomes can be detrimental.

Following these guidelines, the literature review below focuses on demographics, Medicaid, and criminal justice factors that predict subsequent justice system involvement. It also briefly reviews IOC's goals and how these might inform the variable creation process described below. Of note, the literature review provides only a brief summary of the research. Given the limited scope of the project, citations are not provided, but reference articles are available upon request.

1.3.1 Medicaid and Demographic Variables Linked to Criminal Justice Outcomes

Though not specific to the IOC, the review identified several categories of Medicaid variables with established relationships to criminal justice outcomes. Of note, the review below is not intended to make a judgement regarding the underlying causal relationships or the fairness of the relationships; it merely describes associations.

1.3.1.1 Demographic Variables:

- *Age* is consistently associated with criminal justice outcomes across multiple studies, with younger individuals typically having higher recidivism risk.
- *Sex* functions both as a direct predictor of criminal justice outcomes and as a moderating variable that influences how other risk factors affect recidivism.
- *Race and ethnicity* are linked to differential justice system outcomes and may moderate treatment effects, potentially owing to differential treatment by, and/or differential involvement in, the criminal justice system.
- *Housing status*, including homelessness and housing instability, are strongly associated with both criminal justice involvement and healthcare utilization patterns.

1.3.1.2 Mental Health and Substance Use Variables

- *Substance use disorders* are strong predictors of criminal justice involvement, particularly for drug-related and property crimes.
- *Mental illness diagnoses*, especially mood disorders and psychotic disorders, are associated with increased risk of justice involvement and longer jail stays.
- *Co-occurring disorders*, the combination of mental health and substance use issues creates an elevated risk of increased criminal justice involvement.

1.3.1.3 Healthcare Utilization Patterns:

- *Provider diversity*, including the number of doctors seen and the geographic diversity of providers relate, to healthcare access patterns that may affect criminal justice outcomes.
  - Research on healthcare fragmentation indicates that discontinuity of care is associated with worse outcomes for justice-involved individuals with certain health conditions.
  - Studies examining justice-involved Medicaid beneficiaries have found that those with more fragmented care (as measured by number of distinct providers and locations) demonstrate higher rates of recidivism, potentially due to challenges in maintaining treatment consistency. The nature of the IOC, however, might reverse this relationship such that a team of doctors working together collaboratively for patient care might lead to less recidivism or criminal justice contact.
- *Medicaid costs* serve as a proxy for healthcare needs and utilization intensity.
  - Research indicates that Medicaid coverage itself is associated with reduced reincarceration rates. Higher Medicaid expenditures may indicate greater healthcare needs that, when addressed, are associated with reduced criminal justice involvement.
  - A greater number of days on Medicaid has been associated with a reduced number of arrests and jail days.

1.3.1.4 Medication Variables

- *Use of psychotropic medications* is an important mediator of criminal justice involvement for individuals with serious mental illness.
- *Medication consistency* is similarly important, as gaps in medication adherence are associated with increased criminal justice contact.

1.3.2 Variables Related to IOC Goals

Though not mutually exclusive from variables above, variable selection was further informed by the IOC's core objectives. The clinic's potential impact on criminal justice outcomes stems from its focus on addressing underlying factors that often contribute to justice system involvement among vulnerable populations. Many high-utilizers of emergency medical services also experience substance use disorders, serious mental illness, housing instability, and other social determinants of health that increase their risk of criminal justice contact. The variable selection strategy, therefore, prioritized measures relevant to the target population, including, in part:

- High-need and high-cost status, defined by:
  - Multiple chronic health conditions
  - High number of comorbidities
  - Frequent hospitalizations and emergency department visits
  - Multiple provider visits
  - High proportion of healthcare system costs
- Public insurance through Medicaid
- Social or behavioral health concerns, such as:
  - Homelessness or food insecurity
  - Substance abuse disorders
  - Mental health disorders
- Difficulty engaging with the health system, with poorly controlled disease states.

1.3.3 Jail and Criminal Justice Variables

Several criminal justice variables demonstrate strong associations with future criminal justice contact. In this case, however, a limitation is that proxies for these variables utilized below were derived from one source, jail data, which might not represent the full range of proxy variables for all relevant criminal justice predictors.

- *Prior arrests* represent a well-established predictor of future criminal justice involvement. Research on predictive risk assessments consistently identifies prior arrest history as a key predictor of future arrests across different age ranges and populations.

- *Prior Jail Sentence Length* demonstrates a complex relationship with criminal justice outcomes, where findings suggest longer incarceration can lead to both increased and decreased rates of recidivism. These mixed findings suggests that prior sentence length may influence future criminal justice outcomes in ways that warrant its inclusion in propensity score models.

- *Prior warrants* reflect a combination of criminal activity and system avoidance behavior that may relate to future justice system outcomes. Warrants often indicate failure to appear or comply with court orders, which correlate with patterns of continued justice involvement.

- *Public order offenses and obstruction offenses* reflect patterns of authority conflict or system non-compliance that predict future justice involvement. These variables capture dimensions of living in a public space that contribute to recidivism risk independently of other offense types. That is, these variables can sometimes identify individuals who draw the attention of police as a result of being homeless and/or having symptoms of mental illness or substance misuse in public.

- *Property crime offenses* are related to specific recidivism patterns. Property offenses often reflect different criminogenic needs than other offense types.

2 Preparatory Methodology

2.1 Selection

2.1.1 Treatment Group

Due to the timing constraints of historical Medicaid data (which included data from April 1, 2020 forward) and the need for both pre-period and post-period measurements, the analysis was restricted to IOC patients who entered the clinic between April 1, 2021 and December 31, 2023. This allowed for a minimum one-year pre-treatment period and one-year post-treatment follow-up, **resulting in 103 eligible IOC participants out of the original 307.**

> Whether the sample of more recent patients is a representative sample of IOC patients is a limitation that needs to be determined by IOC staff. Given the limited timeframe of Medicaid data, however, it was a necessary restriction.

2.1.2 Control Group

For the control group, and in order to make data processing more tenable, the methodology employed a random sampling approach from the Medicaid population that:

1. Identified all Medicaid beneficiaries not enrolled in IOC.
2. Then randomly selected 15,000 non-IOC Medicaid beneficiaries, providing a potential control-to-treatment ratio of approximately 150:1, while also making the process of extracting diagnosis and drug codes (described below) tenable.
3. Assigned "pseudo start dates" to control cases by sampling from the distribution of actual IOC start dates.

The pseudo-start date approach was implemented to address challenges comparing treatment and control groups in interventions with rolling enrollment, and provided the following benefits:

- *Distribution-Based Assignment*: Control participants were randomly assigned start dates sampled directly from the actual distribution of IOC start dates.
- *Pre/Post Definition*: These dates served as anchors for the one-year pre-intervention and post-intervention periods for both groups, enabling valid comparisons.
- *Temporal Balance*: The method creates balanced cohorts with respect to time, partially controlling for seasonal effects, policy changes, and other time-dependent factors that might confound treatment effects.

- *Literature Support*: The approach follows established methods in program evaluation literature for interventions with rolling enrollment, drawing from the `rollmatch` R package and its authors' methodology.

2.2 Medicaid-Jail Record Linkage

Direct matching between Medicaid and jail data was not possible due to the absence of common unique identifiers and variations in name spellings and demographic information. The methodology implemented probabilistic matching using the `reclin2` package in R.

2.2.1 Matching Process

The linkage procedure involved:

1. *Data Separation*: Split the matching process to address treatment and then control cases.
2. *Data Standardization*: Normalized name formats, dates of birth, and other identifiers.
3. *Implemented Diminutive Matching*: Used custom R code to identify diminutives (e.g., Bob for Robert).
4. *Pair Generation*: Created potential matches based on matching variables.
5. *Comparison Vector Creation*: Calculated similarity scores across multiple fields.
6. *Weight Calculation*: Assigned field-specific weights and penalties based on discriminatory power.
7. *Pair Selection*: Used a greedy algorithm to select the best match for each individual.
8. *Match Verification*: Applied probability thresholds combined with manual examination of match quality.

2.2.2 Matching Results

The probabilistic matching approach between Medicaid and jail data revealed different match rates between the treatment and control groups. Because jail data go back to 2009, the information below provides the number of cases with any jail related event since 2009 and any jail related event in a two-year history since clinic start date or pseudo start date, by group:

- Treatment (IOC) Group:
  - 32 of 103 (31.0%) had a jail related event since 2009.

- 18 of 103 (17.5%) had a jail related event two years prior to clinic start date.

- Potential Control Group:
  - 1,423 of 15,000 (9.5%) potential matched cases had a jail related event since 2009.
  - 511 of 15,000 (3.4%) potential matched cases had a jail related event two years prior to pseudo clinic start date.

This imbalance is not a concern, as it is addressed in the Covariate Balanced Propensity Score (CBPS) matching process further below.

2.3 Medicaid Variable Creation

2.3.1 Diagnoses

Medical diagnosis variables were created by processing ICD-10 diagnosis codes from Medicaid claims using Clinical Classifications Software (CCS) to create clinical categories:

1. Used the `dxpr` package in R to map ICD-10 codes to both broad (Level 1) and detailed (Level 2) categories.
2. Created additional indicators separating key mental health and substance use diagnoses (which are combined at Level 1 in CCS categories).
   - Alcohol-related disorders
   - Substance-related disorders (non-alcohol)
   - Schizophrenia and other psychotic disorders
   - Mood disorders
   - Other mental illnesses
3. Filtered to include only diagnoses occurring within one year prior to clinic start (or pseudo-start for controls).

The most frequent diagnosis categories in the IOC sample included mental illness, diseases of the urinary system, and various chronic conditions.

2.3.2 Procedures

Medical procedures were categorized using Current Procedural Terminology (CPT) codes mapped to clinical categories using the `CCS` package in R:

1. Matched procedure codes to standardized categories.
2. Created 17 binary procedure type indicators.
3. Filtered to include only procedures within the one-year pre-period.

2.3.3 Medications

Pharmacy claims were processed to extract and categorize medications:

1. National Drug Codes (NDCs) were converted to RxCUI identifiers using the National Library of Medicine's (NLM's) RxNorm API.
2. RxCUIs were mapped to VA Drug Classification categories.
3. Binary indicators were created for major medication classes.
4. Data were filtered to include only medications filled within the one-year pre-period.

2.3.4 Healthcare Utilization/IOC-Related Variables

Several healthcare utilization metrics were created from Medicaid claims data:

1. *Provider diversity*: A count of unique healthcare providers (by NPI) seen in the pre-treatment period.
2. *Geographic dispersion*: A count of unique provider ZIP codes in the pre-treatment period.
3. *Healthcare costs*: Sum of different Medicaid payment amounts in the pre-treatment period.
4. *Number of Diagnoses*: Sum of unique diagnoses.
5. *Number of Medications/Devices*: Sum of unique medications and devices.

2.3.5 Demographics

Demographics were extracted from Medicaid eligibility data:

1. Age (calculated at clinic start or pseudo-start date)
2. Sex (coded as Male or Female)
3. Race/ethnicity (recoded to "White", "Minority", and "Unknown/Missing" due to incomplete Medicaid data)
4. Housing status (Homeless, Shelter, Housed, or combinations)

2.4 Jail Variable Creation

For individuals successfully matched to jail data, pre-treatment and post-treatment criminal justice metrics were created. These were calculated as a two-year history (pre-period) and a one year post- or observation period. These calculations addressed cases where bookings crossed the observation window as well as missing release dates and same-day bookings (i.e., book and release).

Variables listed below were calculated as two-year jail histories in all cases, and as one-year observation outcomes for *arrests, days incarcerated, and crime severity*. These variables were used as outcomes and were considered as predictors.

1. *Warrant counts*: Number of unique booking dates for warrants/summons
2. *Charge counts*: Number of unique booking dates with new charges
3. *Charge-type specific counts*: Separate counts for different crime types (e.g., obstruction, property, and public order crimes)
4. *Special flags*: Counts of bookings involving domestic violence, liquor-related offenses, violent offenses, and sex offenses
5. *Crime Severity*: Most severe charge category, from no charge to 1st degree felony.

2.5 Pandemic Stratification

To account for the COVID-19 pandemic's impact on healthcare utilization and criminal justice operations, pandemic severity indicators based on monthly COVID-19 case rates in Salt Lake County were created. These included number of cases, case rates/100,000, deaths, and severity levels (Low, Moderate, High, Severe) based on CDC guidelines. These were aligned with individual clinic start dates to ensure treatment and control groups were balanced with respect to pandemic conditions.

> Of note, it was important to consider these variables because, for the Salt Lake County jail, the pandemic notably altered the frequency and type of booking. Certain low-level offenses were not booked, only cited, which altered the likelihood of a post- clinic start event.

2.6 Final Dataset Integration

The final dataset integrated all sources:

1. IOC program data (treatment status and start dates)

2. Medicaid eligibility information (demographics)
3. Medicaid clinical variables (diagnoses, procedures, medications)
4. Medicaid utilization metrics (providers, costs)
5. Jail metrics (both pre and post periods)
6. Pandemic variables

3 Analytic Methodology

This section outlines the approach to establishing a potential causal relationship between treatment (IOC) and criminal justice outcomes using principal component analysis for data reduction, and covariate balanced propensity score (CBPS) methods to balance treatment and control groups for the generalized linear models outcome analysis.

3.1 Principal Components Analysis (PCA)

Recall from above that predictor variables in the PSM framework are expected to be related to *treatment and the outcome* or only to the *outcome* (but not treatment). Because of this, variables identified in the literature review section above, "Medicaid Variables Linked to Criminal Justice Outcomes", were given special attention. The large number of potential Medicaid variables represent complex healthcare utilization patterns that are useful in determining the likelihood of treatment as well as predicting outcomes. However, a notable challenge was presented by the volume of potential Medicaid predictors.

Principal Components Analysis (PCA) was implemented to reduce dimensionality of these variables. PCA's dimensionality reduction creates a more parsimonious representation of healthcare utilization patterns by reducing a large number of variables to a smaller set of "components." The approach maintains important information about the treatment mechanism and reduces concern about whether individual variables were only related to treatment. The method also inherently addresses multicollinearity because PCA converts correlated variables into orthogonal (uncorrelated) principal components.

3.2 Covariate Balanced Propensity Scores (CBPS)

Propensity Score Matching (PSM) methods represent a group of quasi-experimental methods aimed at determining causality. In this study, Covariate Balanced Propensity Score (CBPS) methods, which hold notable advantages over traditional PSM approaches, were utilized.

CBPS offers significant advantages over traditional PSM by integrating treatment assignment modeling and covariate balance optimization into a single step. Unlike PSM, which is highly sensitive to model misspecification and often requires post-estimation balance checks, CBPS directly optimizes balance through Generalized Method of Moments (GMM) or Empirical Likelihood (EL), ensuring near-zero standardized mean differences and implicitly balancing higher moments (e.g., variances). CBPS also reduces reliance on pruning extreme propensities, preserving sample size.

While King and Nielsen (2019)[1] criticize PSM for increasing imbalance (the "PSM Paradox") and inefficiency, CBPS largely mitigates these issues by improving initial balance, reducing

[1]King, G., & Nielsen, R. (2019). Why propensity scores should not be used for matching. *Political Analysis*, *27*(2), 129-147

model dependence, and lowering bias. However, like PSM, CBPS remains vulnerable to unmeasured confounding and cannot fully replicate the rigor of Randomized Control Trials (RCTs). Despite this, CBPS remains a robust quasi-experimental method for causal inference, particularly in observational studies like evaluating the IOC, where RCTs or alternative designs are impractical.

4 Analyses

The analyses that follow examine a potential causal relationship between IOC participation and criminal justice outcomes, specifically:

1. Post treatment start arrest counts
2. Post treatment days spent in jail
3. Most severe offense post treatment start

4.1 Principal Component Analysis

The PCA of Medicaid and IOC eligibility variables revealed that approximately 70% of the variance could be explained by the first three principal components. These components are not specific to IOC patients. Instead, they represent patterns in Medicaid utilization overall and showed:

- PC1 captured the overall extent of healthcare system engagement and clinical complexity
  - High utilizers (individuals with multiple providers, diagnoses, medications, and widespread service use)
  - Low utilizers (individuals with minimal engagement across these domains)
- PC2 captured a distinction between chronic disease management and acute/symptomatic treatment patterns, where contrasting loadings (i.e., how strongly each original variable contributes to a principal component, positive and negative) revealed a spectrum between:
  - Positive end: Serious chronic conditions associated with higher overall costs
  - Negative end: Treatment of acute or episodic symptoms with specific medication classes (allergies, skin conditions, digestive issues, infections)
- PC3 captured a contrast between cost patterns and specific disease treatment approaches. The dominant negative loading of cost, contrasted with positive loadings for certain conditions, suggests this component captures:
  - Negative end: Unexplained high-cost utilization that might represent fragmented care and without clear diagnostic patterns
  - Positive end: More "efficient" healthcare utilization where costs are proportional to specific documented conditions.

4.2 Covariate Balancing Propensity Scores (CBPS)

The covariate Balancing Propensity Score (CBPS) methodology was implemented to create comparable treatment and control groups given that IOC treatment was not randomly assigned - this created systematic differences between those in the IOC and those who were not. CBPS addresses this by calculating weights for each individual in the dataset, which helps make the treatment and control groups similar across the measured characteristics that might influence both treatment assignment and outcomes. Once applied, these weights allowed for a more balanced comparison of criminal justice outcomes between the two groups.

For the CBPS implementation, two key types of variables were included:

1. PCA components derived from Medicaid and IOC eligibility variables.
2. Confounding variables like housing status, demographics, COVID-19 case rates, and criminal justice variables with known associations with either outcomes only or both treatment and outcomes.

Results of the CBPS process are shown below in two ways. The table below provides detailed balance statistics showing the extent of imbalance/balance before and after estimation:

- Control (Unadj): The average standardized value of each variable in the control group before applying any weighting.
- Treated (Unadj): The average standardized value of each variable in the treatment group before applying any weighting.
- SMD (Unadj): Standardized Mean Difference before adjustment - which shows how different the treatment and control groups are on this covariate, standardized to a common scale.
- Control (Adj): The average standardized value in the control group after applying CBPS weights.
- Treated (Adj): The average standardized value in the treatment group after applying CBPS weights.
- SMD (Adj): Standardized Mean Difference after adjustment - which shows how different the groups remain after weighting.
- % Improvement: The percentage reduction in the absolute standardized difference after applying CBPS weights.

The Standardized Mean Difference (SMD) is considered the most important balance metric, as it provides a standardized measure of the difference between treatment and control groups on a given covariate (regardless of its initial scale). A value less than 0.1 (10%) after

CBPS indicates acceptable balance. Larger differences suggest the groups are not comparable on that characteristic, which could bias results. **In this case, all SMD values are well below .10, with the largest at .04.**

One of the largest improvements in SMDs was for the first principal component, which captured the overall extent of healthcare system engagement and clinical complexity. This makes logical sense, given the component captures much of the intended purpose of the IOC.

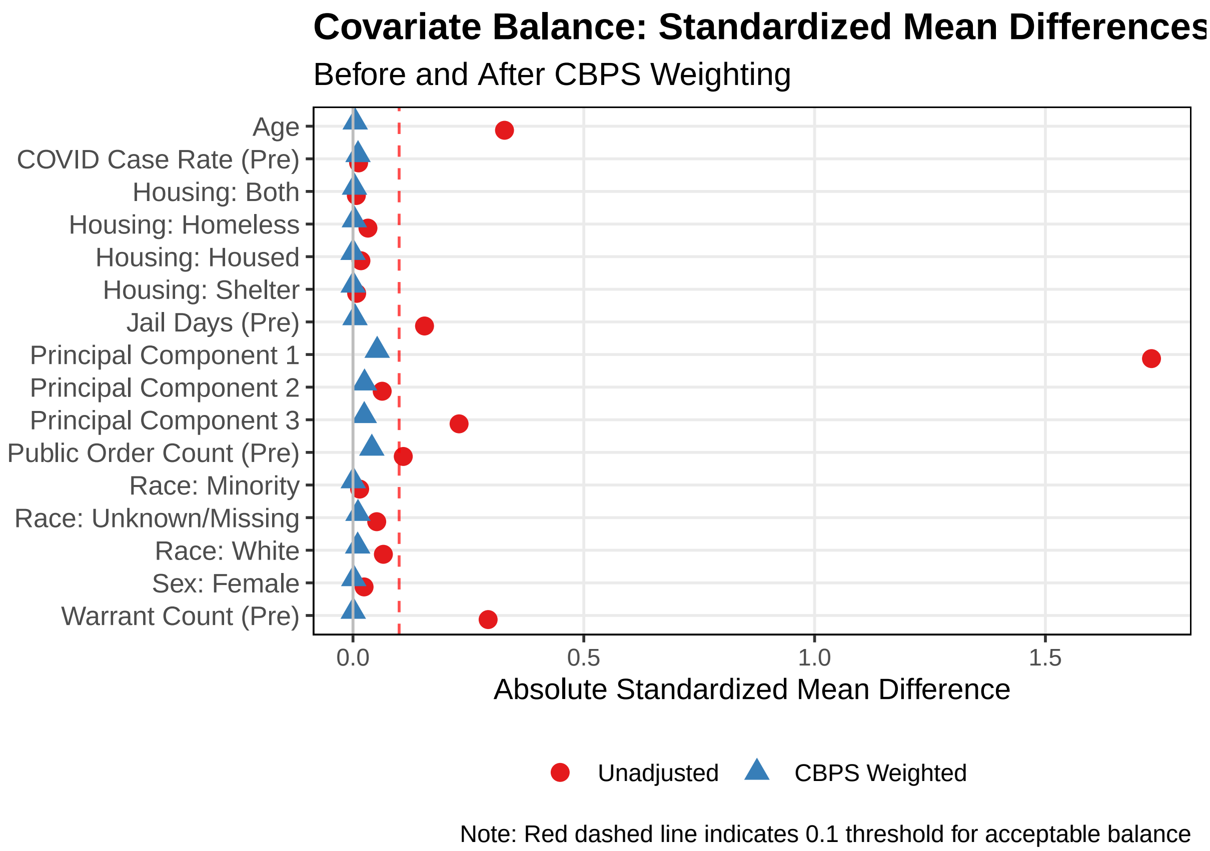
Table 1: Covariate Balance Before and After CBPS Adjustment

	Unadjusted			Adjusted			Improvement
Variable	**Control (Unadj)**	**Treated (Unadj)**	**SMD (Unadj)**	**Control (Adj)**	**Treated (Adj)**	**SMD (Adj)**	**% Improvement**
Age	-0.01	0.27	0.33	0.27	0.27	0.00	98.5
COVID Case Rate (Pre)	0.00	0.01	0.01	0.00	0.01	0.01	10.6
Sex: Female	0.52	0.50	-0.02	0.50	0.50	0.00	92.9
Housing: Both	0.09	0.10	0.01	0.09	0.10	0.00	54.8
Housing: Homeless	0.12	0.09	-0.03	0.09	0.09	0.00	90.9
Housing: Housed	0.79	0.81	0.02	0.81	0.81	0.00	99.5
Housing: Shelter	0.00	0.01	0.01	0.01	0.01	0.00	94.6
Jail Days (Pre)	0.00	-0.10	-0.15	-0.10	-0.10	0.00	97.2
Principal Component 1	0.25	-5.45	-1.73	-5.28	-5.45	-0.05	97.0
Principal Component 2	-0.01	0.12	0.06	0.07	0.12	0.02	60.6
Principal Component 3	0.03	-0.59	-0.23	-0.53	-0.59	-0.02	89.4
Public Order Count (Pre)	-0.01	0.18	0.11	0.11	0.18	0.04	62.6
Race: Minority	0.06	0.05	-0.01	0.05	0.05	0.00	95.2
Race: Unknown/Missing	0.51	0.46	-0.05	0.45	0.46	0.01	79.0
Race: White	0.43	0.50	0.07	0.51	0.50	-0.01	84.7
Warrant Count (Pre)	0.01	-0.15	-0.29	-0.15	-0.15	0.00	99.8

[*] SMD = Standardized Mean Difference

[†] Values < 0.1 indicate good balance

The figure below presents a more basic interpretation that, owing to its ability to quickly summarize the balance improvement, might prove more useful when presenting results. The figure (called a "love plot") shows the SMDs before and after CBPS weighting. Before weighting, many variables (shown as red dots) had standardized differences exceeding 0.1; after weighting, these differences (shown as blue triangles) were all well below this threshold.



4.3 Outcome Model Specification

4.3.1 Distributional Forms

All three dependent variables in this study — arrest counts, jail days, and crime severity — required special distributional considerations because of:

1. *Non-negative integer values*: Outcomes can only take values of 0, 1, 2, etc., with crime severity bounded at an upper limit of seven.

2. *Excess zeros*: A substantial proportion of individuals have zero counts (no arrests, no jail days).

3. *Overdispersion*: The variance of the outcomes exceeds their mean, violating the assumption of standard Poisson count models.

To address these distributional properties, the analysis implemented a comparative modeling approach, evaluating five distributional forms for each outcome:

1. *Negative Binomial*: Addresses overdispersion by including a dispersion parameter that allows the variance to exceed the mean.
2. *Zero-inflated Negative Binomial*: Models the excess zeros through a two-part process, with a binary model for predicting whether the count is zero, and a count model for the non-zero counts.
3. *Hurdle Negative Binomial*: Treats all zeros as coming from a single process, then models positive counts separately using a truncated negative binomial distribution.
4. *Zero-inflated Hurdle Negative Binomial*: Combines zero-inflation and hurdle approaches when modeling distributions.
5. *Zero-inflated Beta-Binomial (ZIBB)*: Accounts for the bounded integer nature of the severity scale (0-7)[2], excess zeros, and potential overdispersion.

R code implemented and tested the fit of these models using the `glmmTMB` package.

4.3.2 Model Selection Criteria and Process

Model selection was conducted using the Akaike Information Criterion (AIC), given AIC balances model fit with parsimony. For each outcome, the code computed AIC values across the four model specifications. The model with the lowest AIC value was selected as the best-fitting specification for each outcome.

The analysis also compared models with and without PCA components included directly in the outcome model. When the PCA components improved model fit (beyond their inclusion in the CBPS weights), they were included in the final models, using a method called "double adjustment". In these data, all models with the PCA components revealed lower AIC values, indicating the principal components captured important variation that remained relevant after weighting.

[2]Although not technically a count variable, crime severity can be modeled using count distributions because of its scaling and integer properties. A caveat to its use is that count distributions do not assume an upper-bound, and the severity variable could not exceed seven. Given this, a zero-inflated beta-binomial (ZIBB) was included in the list of tested distributions.

4.3.3 Diagnostic Assessment

After selecting the best-fitting model for each outcome, the analysis conducted diagnostic checks using the `DHARMa` package in R. These diagnostics included:

1. *QQ plots*: To assess overall model fit by comparing the distribution of standardized residuals to the expected uniform distribution.
2. *Zero-inflation tests*: To verify whether the model adequately accounted for excess zeros.
3. *Dispersion tests*: To check if the variance structure was appropriately modeled.
4. *Residuals versus predicted values*: To identify potential patterns or heteroscedasticity (larger than expected variance).
5. *Outlier identification*: To detect influential observations.
6. *Zero-value prediction tests*: To ensure that the selected models accurately captured the data-generating process for each outcome.

In all cases, only minor violations were identified, and never on more than two of the diagnostic metrics. Because of the large size of the control group, some significant deviations were expected.

4.4 Interpretation of Treatment Effects

4.4.1 Treatment Effect Estimation and Causal Paths

The outcome models in this analysis estimated the **Average Treatment Effect on the Treated (ATT)**. The ATT addresses the question: "For those who received the IOC treatment, what was the effect compared to if they had not received it?" This is different from the Average Treatment Effect (ATE) estimate, which estimates the effect if the entire population had received treatment versus if none had.

The ATT focus is deemed appropriate here because:

1. The study is primarily interested in evaluating the effectiveness of the IOC for the specific IOC patients who actually qualified for and received it.
2. The selection criteria for IOC treatment are complex and target a specific population with multiple health conditions, frequent hospitalizations, social/behavioral health concerns, and high health costs.
3. The CBPS weights create a pseudo-population where control cases are comparable to treated units in terms of covariate distributions.

4.4.2 Causal Path Visualization by Directed Acyclic Graph (DAG)

To solidify concepts, a Directed Acyclic Graph (DAG) is provided below. It provides a visual representation of the causal relationships between the IOC treatment and criminal justice outcomes. Of note, it is a causal visualization and not a diagram of structural paths as in Structural Equation Modeling (SEM).

The DAG consists of five nodes representing different variable groups:

1. *Medicaid Covariates (MC)*: These include health conditions, healthcare utilization metrics, medication categories, and other variables derived from Medicaid records. These variables are used to derive the PCA components.
2. *Criminal Justice Covariates (CJ)*: These capture pre-treatment criminal justice metrics (e.g., days in jail, warrant counts). These influence both treatment assignment and outcomes.
3. *Other Covariates (OC)*: These include demographics (e.g., age, sex, housing status) and COVID case rates. Like the criminal justice covariates, these influence both treatment assignment and outcomes.
4. *Treatment (T)*: This represents enrollment in the IOC (treatment) versus the not treated, matched cases (control).
5. *Outcomes (Y)*: These are the criminal justice outcomes being examined: post-treatment arrest counts, jail days, and crime severity.
6. *PCA Components (P)*: These are the principal components derived from the Medicaid covariates.

The arrows in the DAG represent hypothesized causal relationships:

Confounding Pathways

1. **CJ → T and CJ → Y**: This represents confounding through criminal justice variables. For example, individuals with higher prior arrest rates might be more likely to receive treatment (CJ → T) and also have different post-treatment arrest patterns independent of the treatment effect (CJ → Y).
2. **OC → T and OC → Y**: This represents confounding through other covariates. For instance, age might influence both treatment assignment and criminal justice outcomes.
3. **P → T and P → Y**: This represents confounding through the PCA components derived from Medicaid covariates. These components influence both treatment assignment and outcomes.

Treatment Effect Pathway

T → Y: This arrow represents the causal effect of interest or how IOC treatment directly influences criminal justice outcomes. The goal of the analysis is to isolate this pathway while controlling for the confounding pathways.

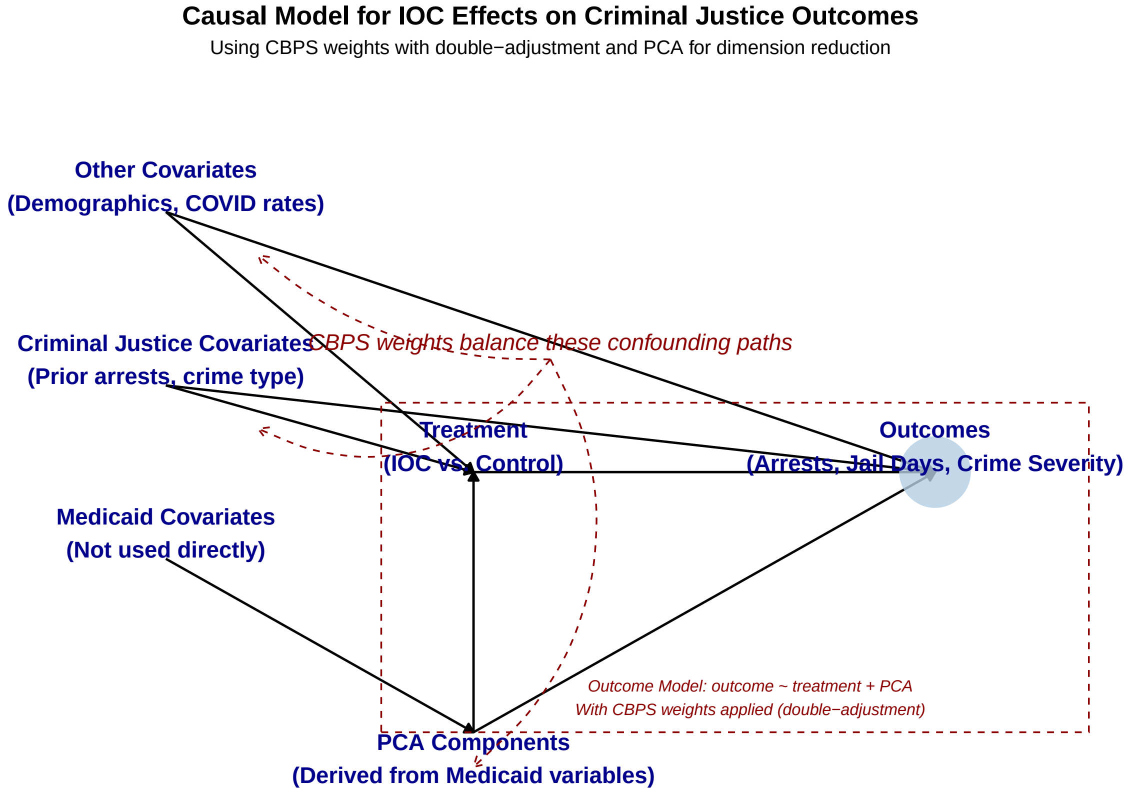
PCA Dimension Reduction Pathway

MC → P: This indicates that the PCA components were derived from the Medicaid covariates.

The DAG structure has several implications for interpreting the analysis results:

1. *Conditional Exchangeability*: The CBPS weights are designed to achieve balance on observed confounders (CJ, OC, and P), supporting the assumption that treatment and control groups would have similar outcomes in the absence of treatment.
2. *Role of Unobserved Confounding*: The DAG only represents observed variables. Any unobserved factors affecting both treatment assignment and outcomes would not be addressed by the CBPS weighting and could still bias results.
3. *Direct vs. Indirect Effects*: The model estimates the total effect of treatment on outcomes, which could operate through various mechanisms not explicitly modeled in the DAG.

To illustrate how the DAG works in practice, consider a patient with multiple chronic health conditions (represented in MC and captured by P) who might be more likely to receive IOC treatment (P → T) and also more likely to have criminal justice involvement due to factors related to their health status (P → Y). Without proper adjustment, comparing their outcomes to those of healthier individuals would produce a biased estimate of the treatment effect. The CBPS weighting addresses this by increasing weights for control cases with similar PCA component profiles to treated patients, creating a more comparable comparison group.



Note: This diagram shows the causal structure. CBPS weights balance confounding from Justice Covariates, Other Covariates, and PCA components. The final regression model includes Treatment and PCA components, weighted by CBPS weights (double−adjustment). Medicaid Covariates are used only to derive PCA components.

4.5 Results

4.5.1 Model Estimates

The first table below show the coefficient ("Estimate") for the treatment effect in each outcome model. These represent the difference in log-expected values between the treatment and control groups, after adjustment for confounding variables. Negative values indicate that IOC treatment was associated with a reduction in the outcome. Standard errors and p-values are also shown. The modeling results presented in the table show that IOC treatment was associated with a significant reduction in arrests and crime severity, and a marginally significant reduction in jail days ($p < .10$).

The next table provides a summary of the results from above that might be more useful for a cost-benefit analysis. Specifically, the table provides the percentage decrease in each outcome associated with IOC participation. It also provides the best-fitting distribution by outcome.

Table 2: Model Results for All Outcomes

	Model Estimates			
Parameter	**Estimate**	**Std. Error**	**p-value**	
Arrests				
Treatment	**-1.23**	0.31	<0.001	***
PC1	**-0.03**	0.05	0.531	
PC2	**0.65**	0.09	<0.001	***
PC3	**0.21**	0.06	<0.001	***
Jail Days				
Treatment	**-0.70**	0.39	0.074	.
PC1	**0.11**	0.06	0.067	.
PC2	**0.52**	0.10	<0.001	***
PC3	**0.17**	0.09	0.073	.
Severity				
Treatment	**-1.29**	0.34	<0.001	***
PC1	**-0.15**	0.05	0.006	**
PC2	**0.35**	0.11	0.002	**
PC3	**0.14**	0.07	0.030	*

Note:
* p<0.05, ** p<0.01, *** p<0.001

Table 3: Treatment Effects Across All Outcomes

	Model Estimates		Model Info
Outcome	**Treatment Effect**	**Interpretation**	**Model Type**
Arrests	-1.23*** (0.31)	Treatment associated with 70.9% decrease in arrests	Zero-Inflated Negative Binomial
Jail Days	-0.70 (0.39)	Treatment associated with 50.2% decrease in jail days	Zero-Inflated Negative Binomial
Crime Severity	-1.29*** (0.34)	Treatment associated with 72.5% decrease in crime severity	Zero-Inflated Beta-Binomial

Note:
Treatment effects shown with standard errors in parentheses. For count models, log coefficients are transformed to percentage changes using the formula: (1-exp(coef))×100%. Negative coefficients indicate a reduction in the outcome associated with treatment.
[*] * p<0.05, ** p<0.01, *** p<0.001

4.5.2 Predicted Probabilities

The values in the final table show the predicted values for each outcome by group, and are also likely useful for a cost-benefit analysis. The table provides these at the person or individual level, and also extrapolated to the current IOC patient size. For example, the predicted number of arrests is less than one at the individual level for both the treatment and control groups, but, extrapolated to the size of the current IOC capacity, the one year difference in arrests is 97 (i.e., 138 - 41). The difference for jail days is notably larger at 2,694.

Severity is not provided at the program level because it is not truly a count variable. It is also rounded to an integer value because of its whole number scaling from 0 - 7. While more accurate given the scaling, the rounding obscures the true predicted difference of 2.1 in the control group and 0.6 in the treatment group. Because of rounding, however, the predicted maximum charge severity for the treatment group is an infraction (coded 1), while, for the control group, it is a class C misdemeanor (coded 2).

Table 4: Predicted Outcomes by Group: Individual and Program Level

		Predicted Values	
Outcome	**Group**	**Individual (95% CI)**	**Program Effect**
Arrests	Control	0.4 (0.2 - 0.9)	138
	Treatment	0.1 (0.1 - 0.3)	41
Jail Days	Control	17.4 (6.6 - 45.6)	5338
	Treatment	8.6 (3.1 - 23.7)	2644
Severity	Control	2 (1 - 4)	–
	Treatment	1 (0 - 1)	–

Note:
Program-level predictions are based on a program size of 307 clients and are not applicable for Severity. All values are rounded to one decimal place for individual predictions and to whole numbers for program predictions.

5 Potential Study Limitations

In any research study, randomized controlled trials included, it is important to document potential limitations so readers can determine for themselves whether results are convincing. In the current study, there are several considerations.

5.1 General Considerations

- *Short Observation Period*: Owing to limitations of historical Medicaid data, the follow-up period was relatively short for the criminal justice outcomes. It is impossible to know whether the observed effect would be maintained, reduced, or augmented over a longer follow-up period.
- *Limited Criminal Justice Metrics*: Reliance solely on jail data may miss other important criminal justice outcomes such as Failure to Appear (FTA) court appearances, court convictions, or probation/parole violations.
- *Limited Sample*: The reduction of eligible IOC participants from 307 to 103 due to data constraints raises the question of whether these more recent patients are representative of IOC patients in general. This could potentially limit generalizability to the full IOC population.
- *Pseudo-Start Date Approach*: While theoretically sound, the assignment of artificial start dates to control participants may not fully capture the complex temporal relationships between program timing and outcomes.
- *Pandemic Period Confounding*: Despite use of variables capturing COVID severity, the COVID-19 pandemic dramatically affected both healthcare utilization and criminal justice operations during the study period in ways that may not be fully controlled.
- *Treatment Heterogeneity*: Because researchers did not receive IOC care records from University of Utah Health Plans (UUHP), the study design could not capture variations in IOC implementation or dosage that could affect outcomes. That is, it was not possible to examine what factors, specifically, might have led to IOC's impact on criminal justice outcomes.
- *Short Follow-up Period*: The one-year post-treatment period may be insufficient to capture longer-term effects of the IOC, particularly for outcomes that develop gradually over time.
- *Causal Inference Challenges*: Despite sophisticated matching methods, non-randomized design cannot eliminate the possibility of selection bias based on unobserved factors that influence both treatment assignment and outcomes.

5.2 Unobserved Confounding Specifically

Because of its importance, the last consideration ("Causal Inference Challenges") deserves additional attention. Though mentioned above when covering the PSM framework, it is worth repeating that CBPS relies on the assumption that there are no unobserved confounders unaccounted for in the data. This issue also relates to the possible limitation raised by the "Treatment Heterogeneity" limitation. Without access to UUHP records, it was impossible to know what variables might moderate the relationship between IOC participation and improved criminal justice outcomes.

For example, there might be motivational differences between patients that lead to improved care and increased use of IOC resources. Highly motivated patients might engage more fully with the IOC, or they might have shown reduced recidivism regardless of IOC participation. Even with perfectly balanced observed covariates through the CBPS process, the estimated treatment effect would capture both the clinic's causal effect and the effect of this unmeasured motivation, potentially inflating apparent clinic effectiveness.

A formal way to test assumptions around some potential unobserved confounders is sensitivity analysis. While the study was not funded for such additional analyses, the greater issue is a lack of UUHP IOC-related data that might inform such an analysis. In the case of motivation (just one hypothetical variable that might be an unobserved confounder), a sensitivity analysis would help determine how strong the effect of motivation would need to be to significantly alter or even invalidate the observed 71% reduction in arrests. If motivation increases the odds of greater IOC participation by a factor of two and independently reduces arrest risk by 30%, the true causal effect of IOC might be closer to a 50% reduction in arrests. At some point, the estimated effect might become statistically non-significant if, as an example, motivation increased greater IOC participation by a factor of three and independently reduced arrests by 40%.

6 Strengths

While study limitations exist, the study employed what might be regarded as the strongest methodological techniques within contextual constraints.

- *Advanced Propensity Score Methodology*: The Covariate Balancing Propensity Score (CBPS) approach represents a significant methodological advancement over traditional propensity score matching, and is substantially more robust against model misspecification. The study achieved excellent balance across all covariates, with all standardized mean differences (SMDs) well below 0.10 (the generally accepted threshold for adequate balance) with the largest being only 0.04. This balance substantially reduces concerns about bias from observed confounders.

- *Effective Dimension Reduction*: The application of Principal Component Analysis (PCA) effectively reduced the dimensionality of Medicaid variables while preserving approximately 70% of the variance in just three components. This approach addressed multicollinearity concerns and also captured complex healthcare utilization patterns that might have otherwise been overlooked. The PCA components provided meaningful insights into healthcare system engagement, disease management patterns, and cost efficiency.

- *Comprehensive Model Selection and Diagnostics*: The study implemented a rigorous approach to model selection (comparing multiple distributional forms and using Akaike Information Criterion (AIC) for selection), which enhances confidence in the final statistical models. The diagnostic checks help validate the three outcome models' ability to account for the unique distributional properties of the criminal justice outcomes analyzed.

- *Consistency across Multiple Outcomes*: The consistency of positive findings across three related but distinct criminal justice outcomes strengthens confidence in the robustness of findings. This pattern of consistent effects across multiple measures makes it less likely that unobserved confounding would affect all outcomes similarly (though it remains possible).

- *Possibility of Substantial Real-World Impact*: Though a cost-benefit analysis is outstanding, the practical implications of the findings are compelling. The IOC model represents a promising approach to improve both healthcare and criminal justice outcomes. The findings suggest that addressing underlying health needs, particularly for high-utilizers of emergency medical services, can substantially reduce criminal justice involvement in the targeted population.

- *Foundation for Future Research*: Despite funding limitations and a lack of UUHP data, the study establishes a foundation for future research. The strong associations between healthcare utilization patterns and criminal justice outcomes warrants exploring other mechanisms of change, including examining specific program moderators, identifying mediators of effects, and conducting formal sensitivity analyses for unobserved confounding.

7 Conclusion

While acknowledging the inherent limitations of observational studies and quasi-experimental approaches, the large effect sizes, consistency across outcomes, and practical significance of the findings, all serve as compelling reasons to further examine the IOC's effectiveness at reducing criminal justice contact. This could be expanded to include Utah Court and Bureau of Criminal Identification (BCI) data to test robustness of findings, but to also consider additional confounders.