

### Abstract

**Motivation**: Opioid Use Disorder (OUD) has become a rampant healthcare issue in the United States of America, claiming 50,000 deaths in 2018.

**Objective:** Determine if there is a causal relationship between various types of rehabilitation and the OUD treatment completion for OUD patients with mental and substance use disorders

#### **Results**:

- L Participation in a detox, 24-hour, hospital inpatient rehabilitation and treatment completion had the strongest causal relationship with treatment completion in patients with co-occurring mental and substance use disorders.
- A Participation in an ambulatory, non-intensive outpatient rehabilitation and treatment completion had the weakest causal relationship with treatment completion in patients with co-occurring mental and substance use disorders.

### Background

- L Since 2000, the number of OUD deaths has sextupled, going from 17,500 to 106,000 in 2021
- **4** 39.0% of OUD patients have co-occurring mental and substance use disorder
- o Of these patients, only 24.5% received help for both disorders
- O These patients are also more likely to get prescribed opioids despite despite their increased risk of addiction and overdose

OUD Patients with Mental Illness



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# Investigating the Impact of Various Opioid Use Disorder **Rehabilitation Services on Treatment Completion for Individuals** with Mental and Substance Use Disorders

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## **Experimental Methods**

# Data Cleaning Feature Selection **Chi-Squared** Test Matching Causal

Inference

Removed individuals and variables with >20% missing/unknown data. Dummied variables to change all data to binary.

Used Logistic Regression, LASSO, and Adaptive Elastic Net to choose variables that are good predictors of treatment. This reduces bias and avoids overfitting.

Used to determine if there is a significant association between selected features and treatment completion status. Selected features that do not have significant association are discarded.

Paired individuals from the treatment group and control group with similar propensity scores, which is the probability of an individual receiving treatment based on its covariates.

Used the propensity score to calculate the Average Treatment Effect of the various rehabilitation services. The quantifies the effect of the rehabilitation services on treatment completion and allows for the causal relationship to be determined.



	Service	Strong Association (P<0.05)	Weak Association (P≥0.05)
1	Detox, 24-hour, hospital inpatient	All Selected Features	N/A
2	Detox, 24-hour, free-standing residential	All Selected Features	N/A
3	Rehab/residential, hospital (non- detox)	All Selected Features	N/A
4	Rehab/residential, short term (30 days or fewer)	Most Selected Features	Full Time Employment
5	Rehab/residential, long term (more than 30 days)	Most Selected Features	Dependent Living Situation
6	Ambulatory, intensive outpatient	Most Selected Features	Dependent Living Situation, Grade 12 (or GED) Education
7	Ambulatory, non-intensive outpatient	Most Selected Features	Dependent Living Situation, Grade 12 (or GED) Education
8	Ambulatory, detoxification	All Selected Features	N/A

### Results

- , Observed strongest causal relationship between Service 1: Detox, 24-hour, hospital inpatient and treatment completion
- Observed the most negative causal relationship between Service 7: Ambulatory, non-intensive outpatient and treatment completion
- L Service 2, 3, 4, 5, 6, and 8 have little to no effect on the rate of treatment completion



## **Conclusion and Future Steps**

• This study proves that OUD patients with co-occurring mental and substance use disorders that participate in 24-hour detox hospital inpatient rehabilitation are most likely to complete their treatment. Moreover, OUD patients with co-occurring mental and substance use disorders that participate in Ambulatory, non-intensive outpatient are least likely to complete their treatment • This study can be used to conduct research on alternate variables in

the Treatment Episode Data Set: Discharges, such as a different population, outcome, or treatment. Treatment providers could also use this data to analyze and focus on one specific rehabilitation service when treating patients with co-occurring mental and substance use disorders

• This information allows us to determine where healthcare providers should spend the most time and resources in order to achieve the most effective results for patients with co-occurring mental and substance use disorders, along with OUD. This study also highlights which areas need to be improved upon.

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