Impact of Referral Source on Treatment Completion Rates Among Patients Suffering from OUD in Substance Abuse Programs

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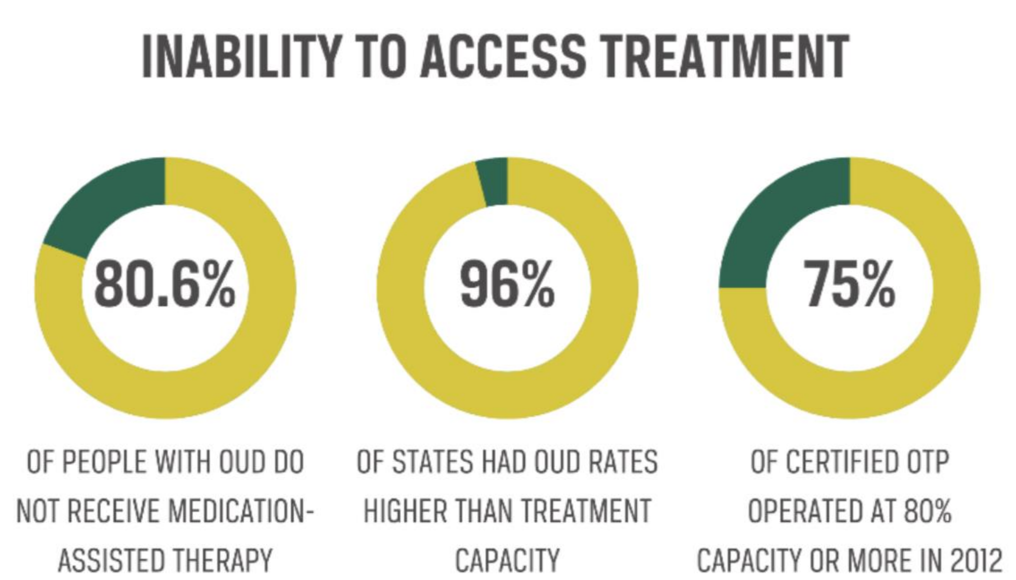
Abstract

Introduction: The opioid epidemic in the USA, with over 90% of overdose-related deaths involving opioids, highlights the urgent need for effective treatment strategies.

Motivation: This study explores how different referral sources influence treatment completion rates in substance abuse programs to improve patient outcomes.



Objective

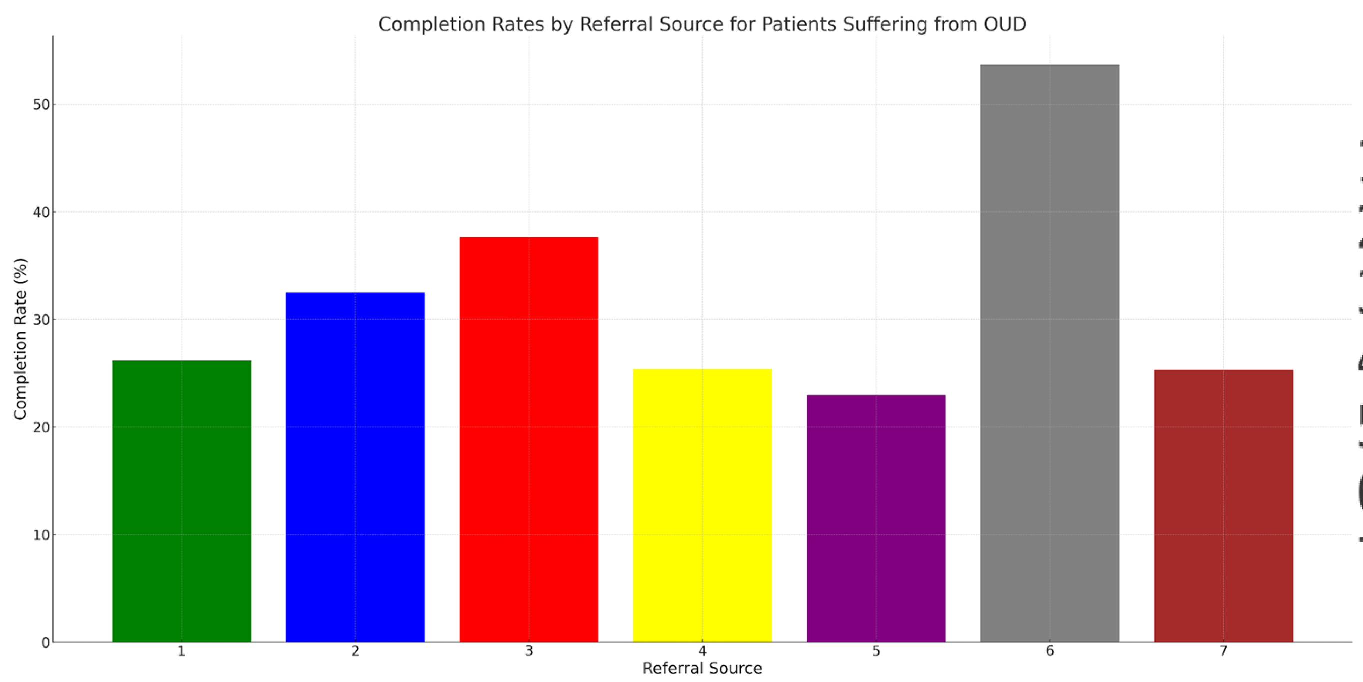
- Evaluate how the source of referral affects the completion rates in treatment programs.
- Identify potential challenges or confounding factors affecting treatment outcomes.

Research

Background: We analyzed patient treatment outcomes for substance abuse disorders using record from the 2015 to 2021 Treatment Episode Dataset: Discharges (TEDS-D). Our goal is to understand how different referral sources (self-referred, healthcare provider, criminal justice, etc.) impact treatment completion. By identifying key factors influencing treatment duration, we aim to improve treatment strategies and outcomes.

Hypothesis: We hypothesized criminal justice referrals would have lower completion rates due to stay lengths and co-occurring disorders. Surprisingly, our analysis showed these factors positively correlated with higher completion rates, challenging our assumptions and suggesting new treatment strategies.

Analysis: Individuals whose highest completed level of education is 'Grades 9 to 11' are 15% more likely to complete the treatment compared to the base level of 'Grade 12 or GED' (OR = 1.15). Those receiving 'Detox, 24-hour, hospital inpatient' services are 10% less likely to complete the treatment compared to the base level of 'Ambulatory, non-intensive outpatient' services (OR = 0.90). Individuals referred by the criminal justice system are 25% less likely to complete the treatment compared to self-referred individuals (OR = 0.75). The ATT value of 0.137 indicates a 13.7% increased likelihood of the outcome for treated individuals. Confounders are adjusted for in the model to isolate the treatment effect.



1 - Individual (includes self-referral)
2 - Court/criminal justice referral/DUI/DWI
3 - Alcohol/drug use care provider
4 - Other health care provider
5 - School (educational)
6 - Employer/EAP
7 - Other community referral

Results

Conclusion: Patients referred by the criminal justice system showed higher treatment completion rates than self-referred patients. Employer-referred patients had the highest completion rates, linked to longer stays. Confounding factors like length of stay and co-occurring disorders revealed strong positive correlations.

Future Plans: Despite current gaps in understanding OUD severity, admission counting biases, and potential unknown confounders, we view these challenges as opportunities for growth. Further research will refine our understanding and improve accuracy, ultimately enhancing efforts to address OUD epidemic.

Statistical Models Used

Chi-Squared test

Excludes variables included: age, gender, marital status, etc.

$$\chi^2 = \sum_i \frac{(o_i - e_i)^2}{e_i}$$

Logistic Regression

Provides the odds ratio if a patient will complete treatment based on a specific variable.

$$\log\left(\frac{p(y=1|x)}{1-p(y=1|x)}\right) = \beta_0 + \beta_1 x_1$$

Outcome Adaptive Elastic Net (OAENet)

Determines the confounding variable for each type of treatment the patient underwent.

$$\textit{Step 1 - Outcome Model: } \hat{\beta}(OLS) = \arg\min_{\beta} \|\mathbf{y} - \mathbf{X}\beta\|_2^2$$
$$= \arg\min_{\beta} l_n(\beta; y, \mathbf{X}) \text{ (MLE of } \beta)$$

$$\textit{Step 2 - Treatment Model: } \hat{\alpha}_{(OAENet)} = \left(1 + \frac{\lambda_2}{n}\right)\left[\arg\min_\beta \left\{ \sum_{i=1}^{n} (-a_i(x_i^T\alpha) + log(1 + e^{x_i^T\alpha})) + \lambda_2 \|\alpha\|_2^2 + \lambda_1 \sum_{j=1}^{p} \hat{w}_j \|\alpha\|_1^1 \right\}\right]$$

Reference

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Treatment Episode Data Set: Discharges (TEDS-D) https://www.datafiles.samhsa.gov/dataset/teds-d-2021-ds0001-teds-d-2021-ds0001

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NSF REU-Site: Research Experience for Undergraduates site to create "Pathways for community college students to enrich their education and careers" (REU - PATHWAYS)

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