Machine learning models of addiction treatment outcomes: An exploratory analysis

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Background and significance

• More Americans will likely die of drug overdose than will die from COVID-19 over the course of the Biden administration.

• Substance use disorder treatment--particularly medication opioid use disorder treatment (MOUD)--is a key, albeit imperfect tool to reduce mortality and morbidity associated with substance use.

• Identifying SUD patients likely to experience unfavorable treatment outcomes may
  • Inform the allocation of harm reduction efforts (e.g. naloxone) to specific subgroups at risk.
  • Generate hypotheses for improved service delivery through provision of complementary or focused resources.
  • Identified features may inform hypotheses or identify specific subgroups for future study designs that inform causal inference.
  • Analyses may inform changing treatment patterns and outcomes over time.

• A growing literature identifies patterns (e.g. poly-substance use) associated with fatal overdose. Less well-known is whether and how these patterns may be associated with adverse treatment outcomes.
Overdose Death Rates Involving Opioids, by Type, United States, 1999-2018

- Any Opioid
- Other Synthetic Opioids (e.g., fentanyl, tramadol)
- Heroin
- Commonly Prescribed Opioids (Natural & Semi-Synthetic Opioids and Methadone)

https://wonder.cdc.gov/
Age-Adjusted Death Rates* Attributable to Alcohol-Induced Causes, † by Race/Ethnicity — United States, 1999–2015

![Graph showing age-adjusted death rates attributable to alcohol-induced causes by race/ethnicity in the United States from 1999 to 2015.](image)
Treatment Episode Data Set (TEDS)

- National data system of annual admissions/discharges from substance use disorder treatment facilities.
- Includes facilities that report to individual state administrative data systems
"Successful" treatment completion

- Detox, 24-hour, hospital inpatient
- Detox, 24-hour, free-standing residential
- Rehab/residential, hospital (non-detox)
- Rehab/residential, short term (30 days or fewer)
- Ambulatory, detoxification
- Rehab/residential, long term (more than 30 days)
- Ambulatory, non-intensive outpatient
- Ambulatory, intensive outpatient

Deaths during treatment

- Detox, 24-hour, hospital inpatient
- Detox, 24-hour, free-standing residential
- Rehab/residential, hospital (non-detox)
- Rehab/residential, short term (30 days or fewer)
- Ambulatory, detoxification
- Rehab/residential, long term (more than 30 days)
- Ambulatory, non-intensive outpatient
- Ambulatory, intensive outpatient

Substances

- Alcohol
- Cocaine/crack
- Methamphetamine/speed
- Marijuana/hashish
- Heroin
- Other opiates and synthetics
- Non-prescription methadone

Completion Rate

Death Rate
Death rate across all treatments by primary/secondary substance

Completion rate across all treatments by primary/secondary substance
Predicting treatment outcomes

Understanding who is succeeding in treatment helps direct resources to those who aren’t.

Binary classification: $y_i \in \{0,1\}$, $X_i = \{\text{demographics, other substances, payment info, etc.}\}$

Goal: Classify unseen sample $y_j$ given $X_j$

Design decisions influence outcomes (e.g. handling missing data)

Training data (75%) → Test → Evaluate performance
Evaluation metrics

Accuracy = \frac{\text{True Positive} + \text{True Negative}}{\text{Total}}

Precision (PPV) = \frac{\text{True Positive}}{\text{True Positive + False Positive}}

Recall (sensitivity) = \frac{\text{True Positive}}{\text{True Positive + False Negative}}

Specificity = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}

Of what the **model labeled positive**, how many were right?
Precision is important when one wants to allocate scarce resources to those with this particular label.

Of **actual positive** samples, how many were correctly identified?

Of **actual negative** samples, how many were correctly identified?
Logistic Regression

\[
\log \left( \frac{p}{1 - p} \right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p
\]

- **Year:** 2018
- **Substance:** Opioids
- **Treatment:** Residential rehab
- **Response:** Treatment completion

Estimated coefficients and standard errors
Logistic Regression vs. "Machine Learning"

- Linear model with interpretable coefficients
- Optimizes for interpretability

- "Black box"
- Optimizes for predictability

$X_i \rightarrow ? \rightarrow \{0, 1\}$
Decision Tree Classifier

\[ X_i = \{ \text{demographics, other substances, payment info, etc.} \} \]

Split the data on the feature that results in the largest information gain.

Tend to **overfit** the training data.
Random Forest Classifier

Variable importance measured by computing how much the tree nodes that use that feature reduce impurity across all trees.

Each node splits on a random subset of features.

Majority wins!

Tune through CV
Beyond Random Forests - Boosting

Original Data → Classifier → Weighted data → Classifier → Weighted data → Ensemble Classifier

By Sirakorn - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=85888769
Predictive boost

- ML methods optimized for better prediction
- Predictive boost consistent but not drastic
- ML framework allows for focus on outcomes, imperative for resource allocation

Year: 2018
Substance: Opioids
Treatment: Residential rehab
Response: Treatment completion
Are they interpretable?

Random Forest variable importance

Coefficients from Logistic regression

Year: 2018
Substance: Opioids
Treatment: Residential rehab
Response: Treatment completion
Substantive questions to answer with TEDS

• How do predictability and emergent predictors differ between substances?
• Has predictability changed over time?
• Can we identify predictors of mortality?
• What are the key differences between short-term rehab and non-intensive outpatient?
• Do secondary substances impact predictability?
<table>
<thead>
<tr>
<th>Substance</th>
<th>Black, non-Hispanic</th>
<th>Hispanic or Latino</th>
<th>White, non-Hispanic</th>
<th>College</th>
<th>High school</th>
<th>No high school</th>
<th>Some college</th>
<th>Some high school</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alcohol</td>
<td>92275</td>
<td>1735</td>
<td>298258</td>
<td>50877</td>
<td>219789</td>
<td>25887</td>
<td>108695</td>
<td>74028</td>
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<tr>
<td>Cocaine</td>
<td>37154</td>
<td>336</td>
<td>39151</td>
<td>4433</td>
<td>43073</td>
<td>5426</td>
<td>17448</td>
<td>20624</td>
</tr>
<tr>
<td>Opioids</td>
<td>58004</td>
<td>1813</td>
<td>368718</td>
<td>23522</td>
<td>252166</td>
<td>27616</td>
<td>104645</td>
<td>93706</td>
</tr>
</tbody>
</table>
Predictability across substances

Year: 2010-2018
Substance: Opioids, Cocaine, Alcohol
Treatment: Residential rehab
Response: Treatment completion
Divisions
- Middle Atlantic
- East South Central
- Medicaid
- Other govt. payments
- No secondary substance
- Private Insurance

Treatment: Residential rehab
Response: Treatment completion
Logistic regression coefficients for Opioids, 2018

- East South Central
- South Atlantic
- West North Central
- Criminal justice referral
- Other income
- Arrested in past 30 days
- Medicaid
- East North Central
- Other govt. payments
- West South Central
- Pacific
- Middle Atlantic
- No charge
- No income
- Female
- Methamphetamine
- Other drugs
- Public assistance
- Some college
- Other opiates
- College degree
- High school degree
- No high school degree
- Non-MOUD
- Heroin
- Healthcare referral
- Prior treatment
- Independent living
- Black
- American Indian
- Other route of administration

Logistic regression coefficients for Alcohol, 2018

- East South Central
- South Atlantic
- East North Central
- Private insurance
- Pacific
- Non-MOUD
- West North Central
- Hispanic or Latino
- Public assistance
- Mexican
- Alcohol care provider
- Independent living
- West South Central
- Arrested in past 30 days
- Non-Hispanic or Latino
- Cuban
- Other source of income
- Other single race
- First use age 25-29

Year: 2018
Treatment: Residential rehab
Response: Treatment completion
Temporal trends

**Year:** 2010-2018  
**Substance:** Opioids, Cocaine, Alcohol  
**Treatment:** Residential rehab  
**Response:** Treatment completion

Averaged across 10 balanced subsamples of 10k observations
Are the predictions fair?

Year: 2010-2018
Substance: Opioids, Cocaine, Alcohol
Treatment: Residential rehab
Response: Treatment completion

Average precision across 10 balanced subsamples of 10k observations
Meth as secondary substance
No secondary substance
West South Central

Treatment: Residential rehab
Response: Treatment completion
Treatment: Residential rehab
Response: Treatment completion
Medicaid expansion
Medicaid expansion

Year: 2010-2018
Substance: Opioids
Treatment: Residential rehab in Medicaid expanded vs. non-expanded states
Response: Treatment completion
"DIVISION" was removed as a predictor
Medicaid expansion

Year: 2010-2018
Substance: Opioids
Treatment: Residential rehab in Medicaid expanded vs. non-expanded states
Response: Treatment completion

![Bar graph showing completion rate by payment source]
Short-term rehab vs. non-intensive outpatient treatment

Variable importance from Random Forest

Year: 2018
Substance: Opioids
Response: Treatment completion
Variables whose importance diverged between groups
• Deaths while in treatment are rare, occurring in only 0.2% of cases
• Non-intensive outpatient deaths account for >80% of all observed deaths across treatments
• Death not so rare in outpatient opioid disorder treatment.
Downsampling for imbalanced classes

When one of the classes makes up just a small fraction of the training data, the model will spend most of its time learning from the other class.

Solution: downsampling
Year: 2018
Substance: Opioids
Treatment: Non-intensive outpatient
Response: Treatment terminated by death
MOUD & Mortality

Year: 2018
Substance: Opioids
Treatment: Non-intensive outpatient
Response: Treatment terminated by death

Motivates further investigation
Conclusions

• Machine learning offers modest but real predictive boost
• Important variables emerge from the model to help direct further analyses
  • Predictability of successful completion of opioid residential treatment has increased since 2010; not true for alcohol/cocaine.
  • Geography consistently emerges as a strong predictor
    • Note for further studies: this could potentially be linked to reporting bias. Should treat carefully.
  • MOUD + age/length of stay linked to opioid mortality—not a causal link, but an important marker and clinical reality in this space.