ScienceDirect

Journal of Substance Use and Addiction Treatment
Volume 164, September 2024, 209435

Exploring predictors of substance use disorder treatment engagement with machine learning: The impact of social determinants of health in the therapeutic landscape

David Eddie [a] [b], John Prindle [c], Paul Somodi [d], Isaac Gerstmann [d], Bistra Dilkina [d], Shaddy K. Saba [c], Graham DiGuiseppi [c], Michael Dennis [e], Jordan P. Davis [f]

Show more

Share Cite

https://doi.org/10.1016/j.josat.2024.209435
Get rights and content

Highlights

- Predictors of substance use disorder (SUD) treatment engagement were explored.
- Random forest machine learning and GLMM were utilized.
- Both individual- and neighborhood-level factors were identified.
- Neighborhood-level measures of socioeconomic marginalization were most predictive.
- Socioeconomic marginalization was associated with poorer SUD treatment outcomes.

Abstract

Background

Improved knowledge of factors that influence treatment engagement could help treatment providers and systems better engage patients. The present study used machine learning to explore associations between individual- and neighborhood-level factors, and SUD treatment engagement.

Methods

This was a secondary analysis of the Global Appraisal of Individual Needs (GAIN) dataset and United States Census Bureau data utilizing random forest machine learning and generalized linear mixed modelling. Our sample (N=15,873) included all people entering SUD treatment at GAIN sites from 2006 to 2012. Predictors included an array of demographic, psychosocial, treatment-specific, and clinical measures, as well as environment-level measures for the neighborhood in which patients received treatment.

Results

Greater odds of treatment engagement were predicted by adolescent age and psychiatric comorbidity, and at the neighborhood-level, by low unemployment and high population density. Lower odds of treatment engagement were predicted by Black/African American race, and at the neighborhood-level by high rate of public assistance and high income inequality. Regardless of the degree of treatment engagement, individuals receiving treatment in areas with high unemployment, alcohol sale outlet concentration, and poverty had greater substance use and related problems at baseline. Although these differences reduced with treatment and over time, disparities remained.

Conclusions

Neighborhood-level factors appear to play an important role in SUD treatment engagement. Regardless of whether individuals engage with treatment, greater loading on social determinants of health such as unemployment, alcohol sale outlet density, and poverty in the therapeutic landscape are associated with worse SUD treatment outcomes.

Introduction

Difficulty engaging individuals in treatment for substance use disorder (SUD) contributes to SUD morbidity and mortality (Arbour et al., 2011; Ilgen et al., 2007). Treatment dropout rates average around 30% in SUD clinical trials (Lappan et al., 2020), and are likely to be higher in clinical settings. Identifying the individual and environmental characteristics that influence treatment engagement has the potential to increase SUD treatment retention, in part by equipping treatment providers and treatment systems with knowledge about who might be at most risk for treatment disengagement.

Toward this end, a substantial body of research has sought to identify predictors of SUD treatment engagement, defined here as the process of initiating, and sustaining participation in the treatment process.

Previous work has identified a number of factors portending SUD treatment engagement including older age (Brorson et al., 2013), greater therapeutic alliance (Goldberg et al., 2020), and previous connection with providers (Naeger et al., 2016). Conversely, factors found to predict poorer treatment engagement include cognitive deficits (Aharonovich et al., 2006), difficulty regulating affect (Papamalis et al., 2020), perceived SUD severity and fewer treatment resources (Dillon et al., 2020), history of physical and sexual abuse (Claus & Kindleberger, 2002), lower treatment motivation (Hiller et al., 2002), greater psychiatric comorbidity (Lind et al., 2019), presence of 'cluster B' personality disorder/s (Zikos et al., 2010), younger age (Siqueland et al., 2002), and Black or African American race (Lappan et al., 2020). Primary substance used has also been implicated as a predictor, with some evidence suggesting primary cocaine and opioid use is associated with lower likelihood of completing treatment (Brorson et al., 2013; Lappan et al., 2020). While this body of research provides a starting point for understanding predictors of treatment engagement, it is notable for its inconsistent findings, and some key limitations. For instance, prior studies have typically assessed a small number of predictors with modest sample sizes, limiting the field's ability to understand which factors convey the most relative influence.

Machine learning approaches are increasingly being utilized in the behavioral sciences because they can offset these limitations by concurrently examining many predictors and identifying those that are most important. Recently, this approach has been leveraged to predict trajectory and severity of SUD (Hu et al., 2020), and SUD treatment completion (Baird et al., 2022) and success (Acion et al., 2017). To our knowledge, however, no study has applied machine learning to understand SUD treatment engagement. Perhaps, however, the greatest limitation of the present literature is the lack of studies on the influence of neighborhood-level, social determinants of health.

The concept of 'therapeutic landscape' explains that the environment surrounding a treatment center can either support or hinder SUD recovery both during and after treatment (Wilton & Deverteuil, 2006). Previously, with this idea in mind, our team explored how neighborhood-level characteristics surrounding SUD treatment centers influenced post-treatment opioid lapses (Davis et al., 2021), with greater neighborhood poverty, greater population density, and a higher homicide rate emerging as the top predictors of shorter latency to opioid use lapse. Although it has previously been shown that treatment programs serving greater proportions of people identifying as Black or African American, as well as people with lower income, have lower treatment completion rates (Lappan et al., 2020), to date it is not known how neighborhood-level factors such as poverty, population density, income disparities, employment rates, the proportion of individuals with public health insurance, and the number of alcohol sale outlets in an area influence SUD treatment engagement.

To begin to address these knowledge gaps, the present study explored associations between both individual- and neighborhood-level factors and SUD treatment engagement in a large sample of people in treatment for SUD in the United States (US). Using the approach previously described by Berkowitz et al. (2019), the present study leveraged both a machine learning technique that can simultaneously examine many predictors across multiple levels of analysis, and generalized linear mixed modelling. One common criticism of machine learning approaches is their 'black box' output, where predictions do not provide meaningful estimates of uncertainty. However, many machine learning methods can be leveraged to complement regression-based approaches, and concurrently handle many variables to better understand factors most strongly influencing an outcome of interest such as treatment engagement.

Given the varied literature to date identifying predictors of treatment engagement, and the large number of variables explored in this study, we did not begin with any focused, a priori hypotheses. We did, however, anticipate a pattern of results in the which variables reflecting greater individual problem complexity (e.g., greater SUD severity and comorbidity) and greater socioeconomic marginalization (e.g., high poverty, greater alcohol sale outlet density) would be associated with poorer treatment engagement.

Section snippets

Design

This was a secondary analysis of the Global Appraisal of Individual Needs (GAIN) dataset (Dennis et al., 2008), which includes individuals in treatment for SUD. To understand how larger contextual factors like the therapeutic landscape influence treatment engagement, we geo-coded each participant based on the address of where they received treatment. Doing this allowed us to link neighborhood-level data derived from the US Census Bureau (2022) to the GAIN data. …

Procedures

The full dataset for this project …

Analytic plan

In this study, we first created a random forest (i.e., an ensemble of classification or decision trees) to identify the most *important* predictors of treatment engagement. Multicollinearity is addressed within random forests when tuning the model by limiting the number of features compared and employing expert domain knowledge to interpret similar feature importances (Chan et al., 2022).

Following this, we tested a generalized linear mixed model that included the top ten variables that emerged …

Sample characteristics

The sample was, on average, 19.6 (SD=8.5) years old, and 27.0% female (n=4278). Over a third (n=6832, 43.0%) of patients were categorized as having subclinical SUD, 3168 (20.0%) had mild or moderate SUD, and 5873 (37.0%) had severe SUD. In terms of primary substance used, 3290 (20.7%) endorsed alcohol, 2544 (16.0%) amphetamines, 725 (4.6%) cocaine, 8484 (53.4%)

marijuana/cannabis, and 830 (5.2%) opioids. Treatment engagement for the sample was 68.8% when assessed at 3-month …

Discussion

There is a pressing need to identify factors that portend treatment engagement to support more focused and streamlined clinical assessments that identify treatment disengagement risk. To date, most research has focused on individual-level factors. In this study we took a novel approach to identifying predictors of SUD treatment engagement using a combination of random forest machine learning and generalized linear mixed modelling, exploring both individual-level factors, and neighborhood-level …

Conclusions

Social determinants of health are important predictors of SUD treatment engagement. Regardless of whether individuals engage with SUD treatment, social determinants of health such as unemployment, alcohol sale outlet density, and income inequality in one's therapeutic landscape are associated with worse substance use at pre-treatment baseline. Although this disparity reduced over post-treatment follow-up, differences remained. Treatment programs will likely retain more individuals in treatment …

Article tweet

@DavidEddiePhD from @RecoveryAnswers and @HarvardMed with colleagues from @USC and @RandCorporation show that social determinants of health in the therapeutic landscape are critical for predicting who engages with #substanceusedisorder treatment. …

Funding sources

David Eddie was supported by NIAAA award K23AA027577-03. NIDA awards also supported Bistra Dilkina, R01DA11323-19; Shaddy Saba, F31DA057105-01; Graham DiGuiseppi, F31DA053779-02; and Jordan Davis, R21DA051802-02. …

CRediT authorship contribution statement

David Eddie: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **John Prindle:** Investigation, Formal analysis, Data curation, Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Paul Somodi:** Data curation, Writing – original draft, Writing – review & editing. **Isaac Gerstmann:** Data curation, Writing – original draft, Writing – review & editing. **Bistra Dilkina:** Conceptualization, Data curation, Formal analysis, …

Declaration of competing interest

David Eddie is on the scientific advisory boards of mental-healthcare companies ViviHealth and Innerworld and is a partner in Peer Recovery Consultants. The remaining authors declare that they have no known potential competing financial or personal interests. …

Recommended articles

References (46)

E. Aharonovich *et al.*
Cognitive deficits predict low treatment retention in cocaine dependent patients
Drug and Alcohol Dependence (2006)

H.H. Brorson *et al.*
Drop-out from addiction treatment: A systematic review of risk factors
Clinical Psychology Review (2013)

D. Eddie *et al.*
From working on recovery to working in recovery: Employment status among a nationally representative United States sample of individuals who have resolved a significant alcohol or other drug problem
Journal of Substance Abuse Treatment (2020)

Z. Hu *et al.*
Analysis of substance use and its outcomes by machine learning: II. Derivation and prediction of the trajectory of substance use severity
Drug and Alcohol Dependence (2020)

M.V. Kiang *et al.*
Robustness of estimated access to opioid use disorder treatment providers in rural vs. urban areas of the United States
Drug and Alcohol Dependence (2021)

S. Naeger *et al.*
Post-discharge treatment engagement among patients with an opioid-use disorder
Journal of Substance Abuse Treatment (2016)

R. O'Brien *et al.*
A random forests quantile classifier for class imbalanced data
Pattern Recognition (2019)

G.J. Stahler *et al.*
Treatment outcome disparities for opioid users: Are there racial and ethnic differences in treatment completion across large US metropolitan areas?
Drug and Alcohol Dependence (2018)

R. Wilton *et al.*
Spaces of sobriety/sites of power: Examining social model alcohol recovery programs as therapeutic landscapes
Social Science and Medicine (2006)

L. Acion *et al.*
Use of a machine learning framework to predict substance use disorder treatment success
PLoS One (2017)

View more references

Cited by (1)

Craving for a Robust Methodology: A Systematic Review of Machine Learning Algorithms on Substance-Use Disorders Treatment Outcomes ↗
2024, International Journal of Mental Health and Addiction

View full text