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Self-help groups and opioid use disorder treatment: An investigation using a machine learning-assisted robust causal inference framework

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A R T I C L E I N F O

Keywords:
Opioid Use Disorder
Treatment completion
Self-help groups
Buprenorphine
Naltrexone
Causal Inference

A B S T R A C T

Objectives: This study investigates the impact of participation in self-help groups on treatment completion among individuals undergoing medication for opioid use disorder (MOUD) treatment. Given the suboptimal adherence and retention rates for MOUD, this research seeks to examine the association between treatment completion and patient-level factors. Specifically, we evaluated the causal relationship between self-help group participation and treatment completion for patients undergoing MOUD.
Methods: We used the Substance Abuse and Mental Health Services Administration's (SAMHSA) Treatment Episode Data Set: Discharges (TEDS-D) from 2015 to 2019. The data are filtered by the patient's opioid use history, demographics, treatment modality, and other relevant information. In this observational study, machine learning models (Lasso Regression, Decision Trees, Random Forest, and XGBoost) were developed to predict treatment completion. Outcome Adaptive Elastic Net (OAENet) was used to select confounders and outcome predictors, and the robust McNemars test was used to evaluate the causal relationship between self-help group participation and MOUD treatment completion.
Results: The machine-learning models showed a strong association between participation in self-help groups and treatment completion. Our causal analysis demonstrated an average treatment effect on treated (ATT) of 0.260 and a p-value < 0.0001 for the robust McNemars test.
Conclusions: Our study demonstrates the importance of participation in self-help groups for MOUD treatment recipients. We found that participation in MOUD along with self-help groups caused higher chances of treatment completion than MOUD alone. This suggests that policymakers should consider further integrating self-help groups into the treatment for OUD to improve the adherence and completion rate.

1. Introduction

In recent years, there has been a significant reduction of opioid prescriptions [1] and an increase in the usage of non-opioid analgesics for pain management. However, despite these efforts an estimated 2.7 million people were reported to be suffering from opioid use disorder (OUD) in the year 2020 resulting in nearly 80,000 deaths in 2022 [2]. Individuals suffering from OUD are at higher risk for overdose-related deaths and other related adverse outcomes [3]. To effectively tackle this crisis, it is imperative to acquire a comprehensive understanding of the factors that contribute to the reduction of opioid-related adverse outcomes. This understanding is essential for developing effective strategies to combat the alarming rise in fatalities.

Medication for opioid use disorder (MOUD), namely buprenorphine, methadone, and naltrexone, are the gold standard for treatment [4]. Longer treatment retention with MOUD is associated with reduced mortality; however, retention rates are low and variable, with 30–50 % reported in most studies [5]. Several studies have investigated the positive impact of MOUD on both retention and treatment completion in diverse settings, such as residential facilities [6] and outpatient specialty treatment [7]. However, these studies often involve only a specific subset of individuals who seek treatment in these settings, resulting in a limited representation of the broader population affected by OUD. Studies have recognized the positive impact of self-help groups as a

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psychosocial treatment for patients undergoing substance-related treatments [8,9]. Research has indicated that combining 12-step meetings or psychosocial counseling with buprenorphine treatment can lead to less opioid use [10] and improved overall quality of life [11]. Notably, a recent study has highlighted the potentially beneficial role of self-help groups [12] in improving treatment retention. However, these studies have not examined the influence that participation in these groups has on treatment completion rates in the context of MOUD. Since MOUD is the gold standard treatment for OUD, it is important to understand the potential synergistic effects of combining MOUD and self-help groups on treatment completion. Combining MOUD with self-help groups has the potential to improve adherence and retention for recovery [13].

To date, there has been a lack of empirical evidence [14] on a nationally representative population that entails in investigation of the causal relationship of self-help groups and the completion of MOUD treatment. To investigate this gap, our study used a nationally representative sample of patients from the Treatment Episode Data Set: Discharges (TEDS-D). We aim to determine if there is a positive causal relationship between participation in self-help groups and completion of MOUD, and if there is an association across various treatment settings, education levels, census divisions, and pre-existing psychological comorbid conditions.

2. Materials and Methods

2.1. Study data

Patient-level deidentified data were obtained from the Substance Abuse and Mental Health Services Administration's (SAMHSA) public data repository (TEDS-D), for the years 2015–2019 [15]. The data are recorded at the time of admission that is defined as the formal acceptance of a client into substance use treatment and at discharge that is defined as the termination of services. The data set contains 75 variables that include demographic information (age, race, housing, and socioeconomic status), substance abuse behavior (type of substance, frequency, and mode of use), and pre-enrollment factors (referral source, prior treatment episodes, and days waiting for treatment). TEDS-D provides information about patients' substance use-related information from facilities that receive public funds (including federal block grants and state substance use agency funds) to provide addiction treatment services. While discharges from all treatment facilities, such as physician offices or community health centers, are not included, the data set captures a broad cross-section of discharges across the U.S.

We confined our sample to adult discharges receiving treatment primarily for OUD (including prescription opioids, non-prescription methadone, and illicit opioids such as heroin and other opiates and synthetics) in an outpatient, residential, or inpatient setting that lasted for at least thirty days. This meant that we excluded patients whose primary substance of abuse included alcohol and other substances. Discharges from detoxification treatment were discarded as it was not considered complete addiction treatment [16]. The final analytic sample size was 157,885 discharges. Fig. 1 contains additional information about the data filtering process.

2.2. Treatment and outcome definition

According to the TEDS-D codebook, MOUD is defined as present if the patient's treatment plan includes methadone, buprenorphine, or naltrexone. Self-help group attendance at discharge is defined as present if the patient had attended any self-help/mutual support groups focused on recovery like Alcoholics Anonymous (AA), Narcotics Anonymous (NA), or at community health centers. Accordingly, treatment (T) is a binary variable set to 0, if the patient received only MOUD treatment and set to 1 if the patient received MOUD treatment and had any frequency of attendance to self-help groups in the 30 days prior to the reference date (the date of discharge). We considered substance use discharge status as the outcome variable. The outcome binary variable was defined as 1 if the treatment was completed, which means that all parts of the treatment plan or program were completed, and 0 for unsuccessful treatment completion if the participant "dropped out of treatment" or was "terminated by facility". The study excluded participants with all other discharge types.

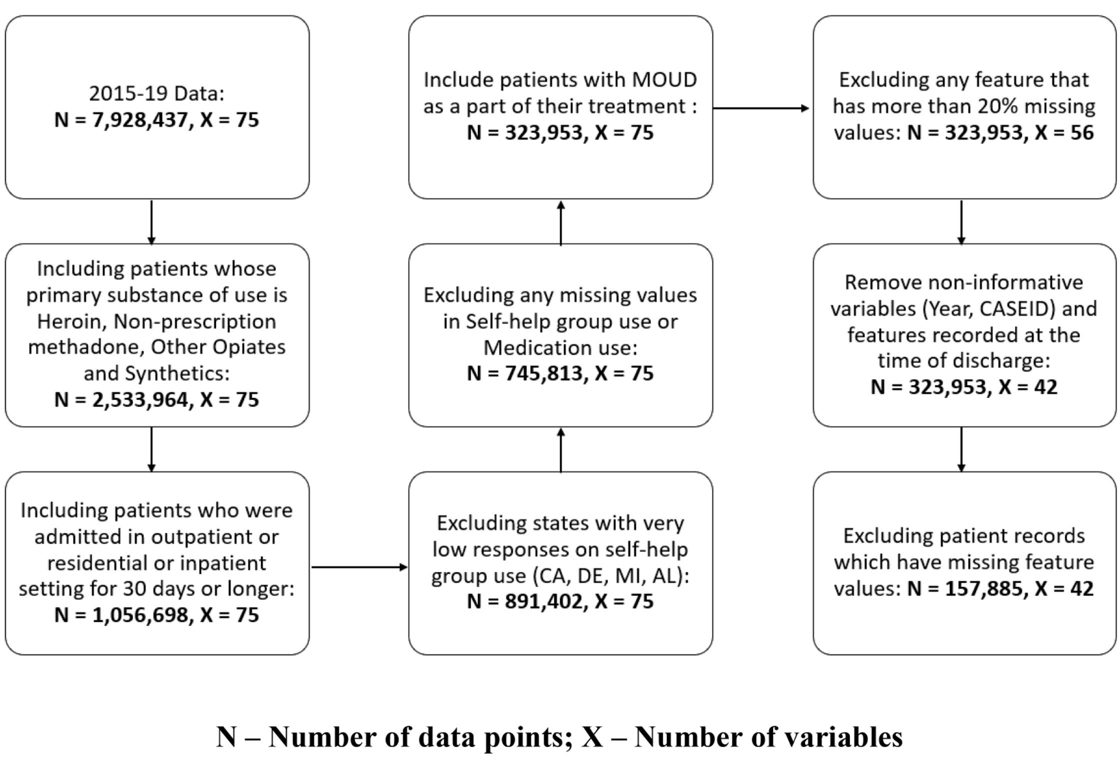

Fig. 1. Steps involved in selecting the final study cohort.

2.3. ML-assisted causal inference framework

Machine learning models are useful in identifying associations between covariates and outcomes, but they fall short of establishing causation. This limitation holds true for various ML techniques such as Lasso Regression, Decision Trees, Random Forest, and XGBoost. To address this challenge of inferring causation, we use causal inference techniques based on observational data. However, a significant obstacle in observational studies is the inability to observe the counterfactual outcomes for the treatment group. We overcome this by matching the treated and control units to ensure the balance of underlying pre-treatment covariates [17] and calculating the treatment effect of the intervention. Due to the high-dimensional nature of this data, finding a good match is almost impossible; therefore, we use an ML-based feature selection technique called Outcome Adaptive Elastic Net (OAENet) [18] to select the confounders by minimizing the bias and variance of the average treatment effect on treated (ATT). Subsequently, we perform classical and robust matching [19] on confounders selected by OAENet to calculate the ATT. Further explanation can be found in the following section.

We designed a novel two-step machine learning (ML) assisted causal inference framework, as seen in Fig. 2, to determine if self-help group participation positively impacted treatment completion. We split out data into 70 %/30 % train and test sets as preprocessing before modeling. The test sets are used to calculate the accuracy metrics for the machine learning models in steps 1 and 2. In step 1, we identified key variables that exhibited significant associations with predicting treatment completion using ML models such as Lasso Regression, Decision Trees, Random Forest, and XGBoost. In the initial phase of step 2, we employed the same ML models listed above to identify the covariates associated with the treatment (T) and outcome (O) variables. A permutation-based approach was employed to identify variables exhibiting a significant association. Through random permutations of predictor variables, their original associations with the response (treatment/outcome) are broken. If a variable originally related to the response is permuted, there is a decline in prediction accuracy. We identify and select variables for causal analysis within the treatment and outcome model that led to a decrease in accuracy > 0. We performed an exhaustive grid search of pre-selected hyper-parameter values for each model. These hyper-parameters were optimized by a ten-fold cross-validated grid search with accuracy set as a scoring method; please refer to Appendix A for more information. The algorithms were assessed based on specificity as the primary criterion, with the area under the curve (AUC) considered in the case of a tie. The choice of specificity stems from the significant cost associated with misclassifying false positives—patients who discontinued their treatment but were inaccurately labeled as completed. All the algorithms above were implemented using the sci-kit-learn machine learning library using Python 3.0.

Selecting and accounting for variables that are confounders and outcome predictors is crucial to enhance the accuracy and reliability of the causal estimate. Confounders are variables associated with both the treatment and outcome (appear in both treatment and outcome models), while outcome predictors are variables associated solely with the outcome (appear only in the outcome model). We used Outcome Adaptive Elastic Net (OAENet) [18] to select for confounders and outcome predictors from the variable selection performed in the initial part of step 2 using ML models. The integration of OAENet aids in mitigating both bias and variance during the matching process. ATT was then calculated using propensity score-based Nearest Neighbor Matching technique to assess the strength of the causal relationship between self-help groups and treatment completion [20]. Lastly, to test if the hypothesized causal relationship was statistically significant and robust to the choice of the matching method, we used Robust McNemar's test Framework. Here we tested our hypothesis:

H_0: There existed no causal relationship between self-help groups and treatment completion.

H_1: There existed a causal relationship between self-help groups and treatment completion.

3. Result

From Table 1 among all discharges (157,885 patients), 45,891 (29 %) completed the treatment. The study sample consisted of 74 % non-Hispanic Whites, 15 % Hispanic/Latino, and 11 % Black individuals. Notably, non-Hispanic Whites exhibited the highest treatment completion rate of 32 % when compared to 21 % and 20 % seen in Black and Hispanic/Latino populations, respectively. 41 % of the sample belonged to the age group 25 to 34, and the second highest representation was from ages 45 and older (24 %). Among the population, 49,058 individuals engaged in self-help groups, with 51 % completing their treatment. In contrast, the remaining 108,827 individuals who did not participate had a lower completion rate, with only 19 % completing their treatment. Table 1 also shows an increasing trend in treatment completion rates, ranging from 23 % to 34 %, corresponding to an increase in the number of years of education. 60 % of patients sought medical care based on self-referral or were referred by a family member or friend. An additional 22 % of the sample received referrals from healthcare providers. There is a contrast in treatment completion rates, with self-referrals having a rate of 23 %, which is significantly lower than the 48 % observed for those referred through the court/criminal justice system.

As seen from Table 2, all the machine learning models exhibit similar performances based on all metrics, except for precision, which shows considerable variation. Notably, the Random Forest model had the highest accuracy (Specificity = 0.93, AUC = 0.76) for predicting treatment completion (outcome). Fig. 3 presents a permutation importance

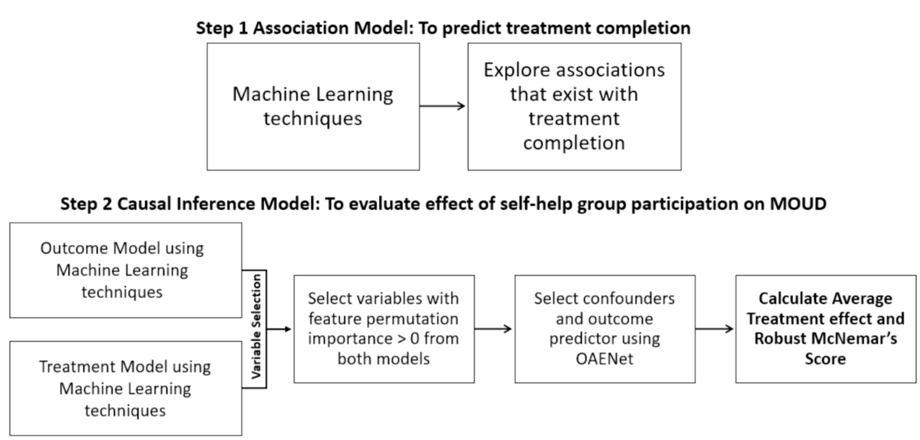

Fig. 2. ML-assisted causal inference framework.

Table 1
Demographics of patients undergoing MOUD.

Variable	All	Treatment Discontinued	Treatment Completed	p-value
GENDER				<0.001
Male	94,556	67,581 (0.71)	26,975 (0.29)	
Female	63,329	44,413 (0.70)	18,916 (0.30)	
RACE/ETHNICITY				<0.001
Black	18,306	14,459 (0.79)	3847 (0.21)	
Non-Hispanic White	116,364	78,936 (0.68)	37,428 (0.32)	
Hispanic/Latino	23,215	18,599 (0.8)	4616 (0.20)	
AGE				<0.001
<18	86	60 (0.70)	26 (0.30)	
18 to 24	15,776	10,808 (0.69)	4968 (0.31)	
25 to 34	65,339	44,848 (0.69)	20,491 (0.31)	
35 to 44	38,247	27,434 (0.72)	10,813 (0.28)	
45+	38,437	28,844 (0.75)	9593 (0.25)	
MARITAL STATUS				<0.001
Never Married	105,937	74,124 (0.70)	31,813 (0.30)	
Now Married	22,929	16,700 (0.73)	6229 (0.27)	
Separated	8712	6511 (0.75)	2201 (0.25)	
Divorced/Widowed	20,307	14,659 (0.72)	5648 (0.28)	
EDUCATION				<0.001
8 YEARS OR LESS	10,053	7752 (0.77)	2301 (0.23)	
9 to 11	32,116	24,068 (0.75)	8048 (0.25)	
12 (GED)	72,999	50,532 (0.70)	22,467 (0.30)	
13 to 15	35,678	24,983 (0.70)	10,695 (0.30)	
16 or MORE	7039	4659 (0.66)	2380 (0.34)	
EMPLOYMENT				<0.001
Full Time	23,402	16,212 (0.69)	7190 (0.31)	
Part-Time	12,212	8678 (0.71)	3534 (0.29)	
Unemployed	58,270	41,567 (0.71)	16,703 (0.29)	
Not in labor force	64,001	45,537 (0.71)	18,464 (0.29)	
SERVICES				<0.001
Detox, 24 HR, Free – Standing Residential	47	34 (0.72)	13 (0.28)	
Rehab/Res, Hospital (non-detox)	54	11 (0.2)	43 (0.80)	
Rehab/Res, Short Term (30 days or fewer)	3757	543 (0.14)	3214 (0.86)	
Rehab/Res, Long Term (more than 30 days)	16,957	8252 (0.49)	8705 (0.51)	
Ambulatory, intensive Outpatient	14,450	7639 (0.53)	6811 (0.47)	
Ambulatory, Non-intensive Outpatient	122,603	95,508 (0.78)	27,095 (0.22)	
Ambulatory, Detoxification	17	7 (0.41)	10 (0.59)	
REFERRAL SOURCE				<0.001
Self-referral	94,449	72,767 (0.77)	21,682 (0.23)	
Medical referral	34,351	22,131 (0.64)	12,220 (0.36)	
Court/Criminal justice referral	17,045	8881 (0.52)	8164 (0.48)	
Other referral	12,040	8215 (0.68)	3825 (0.32)	
COMORBID PSYCOLOGICAL PROBLEM				<0.001
No	75,271	53,987 (0.72)	21,284 (0.28)	
Yes	82,614	58,007 (0.70)	24,607 (0.30)	
Self Help Group				<0.001
Participated	49,058	23,807 (0.49)	25,251 (0.51)	
Did not participate	108,827	88,187 (0.81)	20,640 (0.19)	

Note: All p-values obtained from chi-squared test for independence of categorical variables.

plot obtained from the Random Forest model showing features in decreasing order of association with the outcome. Some of the most important variables for predicting treatment completion were self-help groups, services provided at the time of treatment (rehab, residential treatment, ambulatory services), census division across the U.S, frequency of substance use and referral source.

Table 2
Accuracy metrics for predicting outcome (the number in the parenthesis indicates 95 % CI of the accuracy metrics).

Metric	Lasso Regression	Decision Trees	Random Forest	XGBoost
AUC	0.75 (0.73–0.77)	0.75 (0.72–0.78)	0.76 (0.74–0.78)	0.75 (0.72–0.78)
Brier	0.17 (0.16–0.18)	0.17 (0.16–0.18)	0.17 (0.16–0.18)	0.17 (0.16–19)
Precision	0.72 (0.72–0.72)	0.73 (0.72–0.74)	0.90 (0.90–0.90)	0.74 (0.74–0.74)
Recall	0.37 (0.34–0.41)	0.39 (0.34–0.43)	0.40 (0.36–0.43)	0.40 (0.36–0.44)
Specificity	0.93 (0.92–0.95)	0.93 (0.91–0.94)	0.93 (0.92–0.94)	0.92 (0.90–0.94)

Random Forest Outcome (O) and Random Forest Treatment (T) models (see Appendix B for accuracy metrics for the Treatment model) performed the best when considering specificity and AUC as accuracy metrics. See Appendix C for more information on the calibration curves. From these models, we selected variables with permutation importance > 0, as seen in Table 3. We used OAENet model to select confounders and outcome predictors from the previously filtered variables (listed in Table 3). We have listed the selected confounders and outcome predictors in Table 4.

To calculate the Average Treatment Effect on Treated (ATT), we employed OAENet-selected variables to perform matching of treatment and control distributions. We utilized propensity score matching with the nearest neighbor method resulting in high-quality matches with a standardized mean difference = 0.058 and variance ratio = 1.181. Through this matching process, we obtained matched pairs and calculate the ATT to be 0.260. Overall, involvement in self-help groups caused a 26.0 % improvement in treatment completion rates for OUD patients.

To examine further if participation in self-help groups improved treatment completion, we tested the hypothesis stated in section 2.3 using the Robust McNemars test [19,21] with a level of significance $\alpha = 0.05$. With $B_{max} = 10906$ (number of pairs where treatment unit has outcome = 0 and control unit has outcome = 1) and $C_{max} = 13110$ (number of pairs where treatment unit has outcome = 1 and control unit has outcome = 0), we calculated the robust McNemar's test statistic = -14.22 and its corresponding p-value < 0.0001, confirming that participation in self-help groups for patients undergoing MOUD caused a higher rate of treatment completion.

Based on our analysis outlined in Appendix D, we offer insights into identifying individuals with the highest likelihood of completing their treatment. Utilizing a Lasso Regression Model that incorporates relevant confounders and outcome predictors from OAENet, we calculated the odds ratio (OR) to assess the impact of various patient-level factors. Notably, individuals with 16 or more years of education, of non-Hispanic white ethnicity, with no substance use in the past month (from the time of admission), referred to the treatment facility by the court/criminal justice system and participating in self-help groups exhibit the highest likelihood of completing their treatment.

4. Discussion

Of the variables we studied, participation in self-help groups had the highest association with treatment completion, indicating that incorporating self-help groups into the MOUD treatment plan has the potential to improve rates of treatment completion. Another important association found was the type of medical service setting (Rehab / Residential, Ambulatory intensive/non-intensive) where the patient was treated, which can play an important role in recovery [13]. Geographical disparities, which hinder medication access, have been extensively studied as a barrier to recovery [22], and our study identified census divisions as one of the significantly related factors. Further analysis of

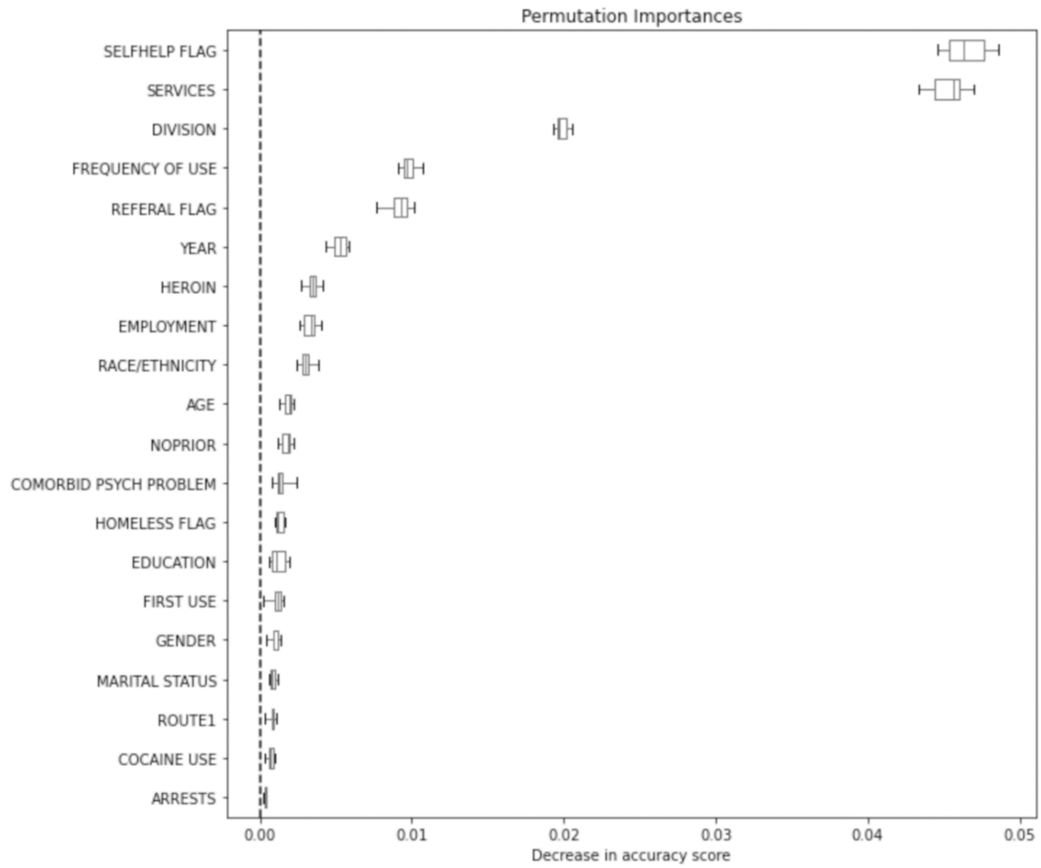

Fig. 3. Permutation importance plot values from Random Forest Outcome model.

Table 3
Variables selected from both treatment and outcome models with permutation importance > 0.

Variables	Variable Definition
Services	Service setting at admission
Division	Census Division
First use	Age at first use
Year	Year of discharge from substance use treatment
Referral	Treatment referral source
Frequency	Frequency of drug use at admission
Education	Education Level
2nd Substance	Substance use at admission (secondary)
Employ	Employment Status
Age	Age at admission
Marital Status	Marital Status
Route of 1st Substance	Route of Opioid Intake (Inject or Not)
Race/Ethnicity	Race/Ethnicity
Comorbid Psychological	Comorbid psychological Problem
Gender	Male/Female
No Prior	Indicates the number of previous treatment episodes the client has received in any substance use treatment program
Homeless Flag	Client having no fixed address, including homeless shelters
Arrests	30 days prior to the date of discharge
VET	Veteran Status
Inject Flag	Route of admission of substance
Cocaine Use	Secondary, or tertiary substance abuse
Heroin Use	Secondary, or tertiary substance abuse
Marijuana Use	Secondary, or tertiary substance abuse
Alcohol Use	Secondary, or tertiary substance abuse
Benzodiazepine Use	Secondary, or tertiary substance abuse
Methamphetamine Use	Secondary, or tertiary substance abuse
Hallucinogen Use	Secondary, or tertiary substance abuse

Table 4
Confounders and outcome variables selected by OAENet.

Covariates	Description
Services	Rehabilitation/Residential, Outpatient patient treatment services
Educ	Number of years of school completed (<8, 9–11, 12, 13–15, >16)
Freq1	Frequency of use of the primary substance at admission (no use in the past month, some use, daily use)
No Prior	Indicates the number of previous treatment episodes the client has received in any substance use treatment program
Comorbid Psychological Problem	If the client has a psychiatric problem in addition to his or her alcohol or drug use problem
Referral Source	person or agency referring the client to treatment
Age	Calculated from date of birth and date of admission
Race/Ethnicity	Identifies the client's race
Inject Flag	Route of administration of the corresponding to primary substance
Marijuana Use	Secondary, or tertiary substance abuse
Alcohol Use	Secondary, or tertiary substance abuse
Benzodiazepine Use	Secondary, or tertiary substance abuse
Methamphetamine Use	Secondary, or tertiary substance abuse

how these factors influence treatment completion rates requires additional analysis and investigation.

In our study, we found that utilization of self-help groups in conjunction with MOUD was low and had high variation between census divisions. The New England region had the highest utilization of self-help groups (40 %), and Puerto Rico had the lowest (4 %). The limited usage of self-help groups may stem from the fact that programs such as Narcotics Anonymous (NA) do not view the use of medications like methadone or buprenorphine as periods of sobriety [10]. These medications are viewed as pharmacological opioids, which can create barriers to participation for individuals on MOUD in these programs.

The results from our study indicate that utilization of self-help groups had a significant positive impact on MOUD treatment completion. It is important to recognize that self-help groups have the potential to enhance the spiritual dimensions of recovery. Fellowships such as NA conduct regular group meetings offering social support and facilitating shifts in beliefs and behaviors. Participation in 12-step groups/mutual support groups views addiction rehabilitation through a spiritual lens, where the goal is to bring about personal changes in an individual's thinking and the feeling of connectedness to oneself and others [23]. Encouraging participation in these groups can provide valuable support and complement the benefits of MOUD treatment [24]. Therefore, it is important to encourage patients undergoing MOUD treatment to participate in these groups.

To fully harness the potential benefits of these two treatment modalities, policy changes appear necessary at multiple levels. First, national fellowships such as Narcotics Anonymous (NA) and Alcoholics Anonymous (AA) should encourage the integration of MOUD treatment within their treatment programs. We believe that these fellowships should recognize, support, and incentivize individuals to engage in MOUD, ensuring they are welcomed and included in the programs. By destigmatizing MOUD treatment, we can increase engagement and active participation in these national-level fellowships. Secondly, local treatment centers can incorporate self-help group sessions as part of their comprehensive treatment approach. As more Medicaid programs cover services like self-help groups, it becomes increasingly important to integrate these sessions into the treatment plans to ensure broader accessibility and availability. Lastly, it is essential to measure and evaluate the impact of combining these treatments across different demographic groups. By studying the outcomes and experiences of diverse populations, valuable insights can be gained to inform future treatment strategies and tailor targeted interventions. Having said that, this study is a preliminary causal observational study designed to examine the effects of combining MOUD with self-help groups on treatment completion. While the findings provide valuable insights, the cross-sectional data's limitations make it challenging to establish the chronological order of these services (i.e., self-help group attendance may precede MOUD treatment). Future research can evaluate longitudinal designs to study the effects of the interventions.

Our study is subject to several limitations. Firstly, the TEDS system, being admissions-based, counts each movement into a different service type/setting for the same individual separately. This may result in inflated discharge numbers and potentially affect the representativeness of the data. Secondly, the dataset may lack crucial unobserved confounders, which can introduce bias to the study results. Thirdly, the data did not provide information on the distinct roles of providers that may have influenced or restricted patient treatment options. Fourthly, the data lacked specificity regarding the types of self-help groups, which encompass a wide range of recovery programs with varying views on medication treatment. Lastly, we lacked information on the severity of patients' conditions and specific MOUD received by them, which could have impacted their treatment outcomes.

5. Conclusion

In conclusion, our study provides insights regarding the retention of MOUD treatment. We found that self-help group utilization rates are generally low and vary significantly across census divisions. Our results strongly suggest that bimodal treatment, combining MOUD with self-help groups, improves treatment retention. By taking necessary action to promote the utilization of self-help groups alongside MOUD, the effectiveness of treatment programs may be improved.

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During the preparation of this work the author(s) used ChatGPT in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Summary Table

Known on topic:	Study added to knowledge:
• Medication for opioid use disorder (MOUD) is very effective to treat OUD. • Longer treatment retention with MOUD is associated with improved mortality; however, retention rates are low and variable.	• Participation of self-help group improves MOUD treatment retention. • Promoting self-help groups alongside MOUD can improve treatment program effectiveness.

CRediT authorship contribution statement

Sahil Shikalgar: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Scott G. Weiner:** Writing – review & editing, Validation. **Gary J. Young:** Writing – review & editing, Validation. **Md. Noor-E-Alam:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A: Fine-tuning hyperparameters for ML optimization

In this section, we delve into the process of fine-tuning hyperparameters of our machine learning models. Here, we provide a detailed account of our approach to hyperparameter optimization, ensuring that our models are finely tuned to deliver the best possible results. We use 10-fold cross-validation to optimize our hyperparameters listed below.

Table A1
Full specification of Hyper-parameters used in ML models.

Machine Learning Model	Hyper-Parameter Tuned	Range of Hyper-Parameters
XGB	colsample_bytree	0.3, 0.5, 0.8
	reg_alpha	0, 0.5, 1, 5
	reg_lambda	0, 0.5, 1, 5
Random Forest	n_estimators	90,100,115,130,150
	criterion	'gini', 'entropy'
	min_sample_leaf	1,2,3,4,5
	min_sample_split	8,10,12,18,20,16
	max_features	'auto', 'log2'
Decision Trees	max_deapth	3,5,7,10,15,20,25,35
	min_sample_leaf	3,5,10,15,20
	min_sample_split	8,10,12,18,20,16
	criterion	'gini', 'entropy'
Lasso Regression	max_iter	100, 125,150,175,200
	solver	'liblinear', 'saga'
	penalty	'l1'

Appendix B: Accuracy metrics for the treatment model

Table B1
Accuracy metrics for predicting treatment (the number in the parenthesis indicates 95 % CI of the accuracy metrics).

Metric	Lasso Regression	Decision Trees	Random Forest	XGBoost
AUC	0.75 (0.72–0.78)	0.77 (0.75–0.80)	0.78 (0.76–0.80)	0.78 (0.76–0.81)
Brier	0.17 (0.16–0.19)	0.16 (0.15–0.18)	0.15 (0.16–0.17)	0.16 (0.15–17)
Precision	0.64 (0.64–0.64)	0.69 (0.69–0.70)	0.87 (0.87–0.87)	0.71 (0.71–0.71)
Recall	0.37 (0.33–0.41)	0.45 (0.40–0.50)	0.41 (0.37–0.46)	0.45 (0.30–0.50)
Specificity	0.91 (0.90–0.92)	0.90 (0.89–0.91)	0.91 (0.91–0.92)	0.90 (0.89–0.91)

Appendix C: Calibration curves for ML models

Calibration curves in the context of classification machine learning models are used to assess the relationship between the predicted probabilities of a model and the actual outcomes or true probabilities. Below we present the calibration curves for the four models that were used in the study.

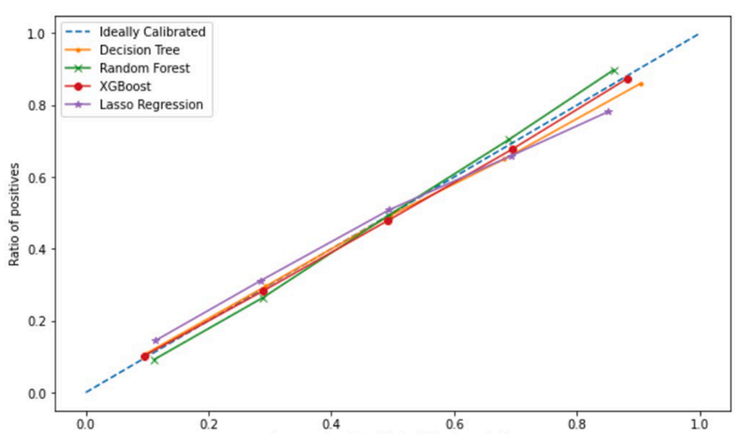

Fig. C1. Calibration curves for ML models

Appendix D: Results of logistic regression for identifying the patient subgroup likely to complete treatment

A Lasso regression model was developed using the confounders and outcome predictors identified by OAENet. This model aims to determine the odds ratio (OR), providing insight into the ideal characteristics of individuals most likely to complete the treatment. If the OR of a patient-level factor is > 1 (upper and lower bounds of CI), then we can say that they are more likely to complete the treatment when compared to the reference (ref) factor. For example, the odds ratio of participation in self-help groups is 3.12, this tells us that a patient is 3.12 times more likely to complete treatment if they participate in self-help groups when compared to those who do not.

Table D1
Odds ratio for the Lasso Regression model.

Variable	Lasso Regression Odds Ratio (OR)	CI (low)	CI (upper)	*p*
Education				
8 YEARS OR LESS	0.70	0.67	0.74	<0.001
9 to 11	0.80	0.78	0.83	<0.001
12 (GED)	(ref)			
13 to 15	0.93	0.90	0.96	<0.001
16 or MORE	1.16	1.09	1.22	<0.001
Race/Ethnicity				
Hispanic/Latino	(ref)			
Non-Hispanic White	1.8	1.73	1.87	<0.001
Black	1.04	0.99	1.10	<0.001
Frequency of Substance use				
No use in the past month	2.01	1.96	2.07	<0.001
Some use	1.26	1.22	1.30	<0.001
Daily use	(ref)			
Referral Source				
Self-referral	(ref)			
Medical referral	1.06	1.03	1.10	<0.001
Court/Criminal justice referral	1.87	1.80	1.95	<0.001
Other referral	1.17	1.12	1.22	<0.001
Self Help Group				
Did not participate	(ref)			
Participated	3.12	3.04	3.21	<0.001

References

[1] Gery P. Guy Jr *et al.*, “Morbidity and Mortality Weekly Report,” 2015. Accessed: Apr. 17, 2023. [Online]. Available: https://www.cdc.gov/mmwr/volumes/66/wr/mm6626a4.htm.
[2] Center for Disease Control, “Opioid Use Disorder | Disease or Condition of the Week | CDC,” Center for Disease Control. Accessed: Apr. 17, 2023. [Online]. Available: https://www.cdc.gov/dotw/opioid-use-disorder/index.html.
[3] R. A. Rudd, N. Aleshire, J. E. Zibbell, and R. M. Gladden, “Increases in Drug and Opioid Overdose Deaths-United States, 2000-2014,” 2016. Accessed: Apr. 17, 2023. [Online]. Available: https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6450a3.htm.
[4] B. E. Biondi, X. Zheng, C. A. Frank, I. Petrakis, and S. A. Springer, “A Literature Review Examining Primary Outcomes of Medication Treatment Studies for Opioid Use Disorder: What Outcome Should Be Used to Measure Opioid Treatment Success?,” *American Journal on Addictions*, vol. 29, no. 4. Wiley Blackwell, pp. 249–267, Jul. 01, 2020. 10.1111/ajad.13051.
[5] B. Chan, et al., Retention Strategies for Medications for Opioid Use Disorder in Adults: A Rapid Evidence Review, J Addict Med 15 (1) (Jan. 2021) 74–84, https://doi.org/10.1097/ADM.0000000000000739.
[6] G.J. Stahler, J. Mennis, The effect of medications for opioid use disorder (MOUD) on residential treatment completion and retention in the US, Drug Alcohol Depend 212 (Jul. 2020) 108067, https://doi.org/10.1016/j.drugalcdep.2020.108067.
[7] N. Krawczyk, A.R. Williams, B. Saloner, M. Cerdá, Who stays in medication treatment for opioid use disorder? A national study of outpatient specialty treatment settings, J Subst Abuse Treat 126 (Jul. 2021), https://doi.org/10.1016/j.jsat.2021.108329.
[8] American Society of Addiction Medicine, The ASAM National Practice Guideline for the Treatment of Opioid Use Disorder: 2020 Focused Update, J Addict Med 14 (2S) (Mar. 2020) 1–91, https://doi.org/10.1097/ADM.0000000000000633.
[9] W. Mohamed, A. Bhandari, R. Mohamed, S. Wen, and R. Bhandari, “Self-Help Group Attendance-Associated Treatment Outcomes Among Individuals With Substance Use Disorder in Short-Term Residential Facilities,” 2022.
[10] L.B. Monico, J. Gryczynski, S.G. Mitchell, R.P. Schwartz, K.E. O’Grady, J.H. Jaffe, Buprenorphine Treatment and 12-step Meeting Attendance: Conflicts, Compatibilities, and Patient Outcomes, J Subst Abuse Treat 57 (Oct. 2015) 89–95, https://doi.org/10.1016/j.jsat.2015.05.005.
[11] D.W. Raisch, et al., Health-related quality of life changes associated with buprenorphine treatment for opioid dependence, Qual. Life Res. 21 (7) (Sep. 2012) 1177–1183, https://doi.org/10.1007/s11136-011-0027-0.
[12] M.R. Stenersen, K. Thomas, C. Struble, K.E. Moore, C. Burke, S. McKee, The impact of self-help groups on successful substance use treatment completion for opioid use: An intersectional analysis of race/ethnicity and sex, J Subst Abuse Treat 136 (May 2022), https://doi.org/10.1016/j.jsat.2021.108662.
[13] H. Wen, B.G. Druss, B. Saloner, Self-help groups and medication use in opioid addiction treatment: A national analysis, Health Aff 39 (5) (May 2020) 740–746, https://doi.org/10.1377/hlthaff.2019.01021.
[14] K. Dugosh, A. Abraham, B. Seymour, K. McLoyd, M. Chalk, D. Festinger, A Systematic Review on the Use of Psychosocial Interventions in Conjunction with Medications for the Treatment of Opioid Addiction, J Addict Med 10 (2) (2016) 93–103, https://doi.org/10.1097/ADM.0000000000000193.
[15] SAMHSA, “TEDS-D-2019-DS0001 (TEDS-D-2017-DS0001) | SAMHDA,” Substance Abuse and Mental Health Services Administration. Accessed: Apr. 17, 2023. [Online]. Available: https://www.datafiles.samhsa.gov/dataset/teds-d-2017-ds0001-teds-d-2017-ds0001.
[16] SAMSHA, *TIP 45: Detoxification and Substance Abuse Treatment*. 2015.
[17] Greenwood and Ernest, Experimental sociology: A study in method, Columbia University Press, 1945.
[18] M. S. Islam and Md. Noor-E-Alam, “Feature Selection for Causal Inference from High Dimensional Observational Data with Outcome Adaptive Elastic Net,” Nov. 2021, [Online]. Available: http://arxiv.org/abs/2111.13800.
[19] M. Morucci, Md. Noor-E-Alam, C. Rudin, A robust approach to quantifying uncertainty in matching problems of causal inference, INFORMS Journal on Data Science 1 (2) (Oct. 2022) 156–171, https://doi.org/10.1287/ijds.2022.0020.
[20] E.A. Stuart, Matching methods for causal inference: A review and a look forward, Stat. Sci. 25 (1) (Feb. 2010) 1–21, https://doi.org/10.1214/09-STS313.
[21] M.S. Islam, M.S. Morshed, G.J. Young, M. Noor-E-Alam, Robust policy evaluation from large-scale observational studies, PLoS One 14 (10) (2019) Oct, https://doi.org/10.1371/journal.pone.0223360.
[22] K. Patel, S. Bunachita, A.A. Agarwal, A. Lyon, U.K. Patel, Opioid use disorder: treatments and barriers, Cureus (Feb. 2021), https://doi.org/10.7759/cureus.13173.
[23] G. Chen, Social support, spiritual program, and addiction recovery, Int J Offender Ther Comp Criminol 50 (3) (Jun. 2006) 306–323, https://doi.org/10.1177/0306624X05279038.
[24] E. Krupitsky, et al., Articles Injectable extended-release naltrexone for opioid dependence: a double-blind, placebo-controlled, multicentre randomised trial, Lancet 377 (2011) 1506–1519, https://doi.org/10.1016/S0140.