

# Predicting Opioid Use Disorder and Associated Risk Factors in a Medicaid Managed Care Population

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**M**edicaid plays a vital role in providing health care services to low-income populations disproportionately affected by the opioid epidemic in the United States. More than 2 million nonelderly adults have been diagnosed with opioid use disorder (OUD), and approximately 47,600 overdose deaths occurred in 2017.<sup>1</sup> OUD is defined as a persistent and problematic pattern of opioid use, characterized by the inability to reduce or stop consumption and/or interference with work and life responsibilities.<sup>2</sup> Of all nonelderly adults diagnosed with an OUD, 38% rely on Medicaid for health insurance.<sup>3</sup> This is more than twice the national proportion of nonelderly adults enrolled in Medicaid (0.15).<sup>4</sup> Medicaid beneficiaries are also at increased risk of opioid-related overdose, particularly as cheaper and more lethal alternatives to prescription drugs (such as heroin and fentanyl) become available.<sup>5,6</sup> To combat this problem, Medicaid spending on OUD-related medications increased by 250% and spending on mental health treatment is anticipated to soar by an additional \$19.49 billion between 2014 and 2020.<sup>7,8</sup> Despite the growing investment in programs and interventions, the rate of OUD and opioid-related deaths remains high.

At AmeriHealth Caritas, a national Medicaid managed care organization (MCO), we developed an Opioid Blueprint to reduce the magnitude of the epidemic among our members. The Opioid Blueprint targets interventions at the pharmacy, provider, and member levels. We have established programs that have successfully reduced the overall number of opioid prescriptions while increasing the availability of medications for OUD. Although progress has been made, we saw an opportunity to more proactively identify and address physical, behavioral, and social risk factors of OUD.

To do so, we aimed to leverage data in new ways to proactively engage our membership and reduce adverse events. We decided to use machine learning to generate actionable insights into OUD risk factors and to prioritize our Medicaid populations for outreach. Researchers have used machine learning methodologies to discover that, in general and commercial populations, individuals with a mental health diagnosis, HIV, hepatitis C, substance use disorder, and tobacco use had greater odds of OUD and/or risk of overdose.<sup>9-12</sup> Machine learning was also successfully used to

## ABSTRACT

**OBJECTIVES:** Medicaid managed care organizations are developing comprehensive strategies to reduce the impact of opioid use disorder (OUD) among their members. The goals of this study were to develop and validate a predictive model of OUD and to predict future OUD diagnosis, resulting in proactive, person-centered outreach.

**STUDY DESIGN:** We utilized machine learning methodology to select a multivariate logistic regression and identify predictors.

**METHODS:** Using 2016-2018 data, we used a staged approach to test and validate the predictive accuracy of our model. We identified OUD, the dependent variable, using an industry-standard definition. We included a series of patient demographic, chronic condition, social determinants of health (SDOH), opioid-related, and health utilization indicators captured in administrative data.

**RESULTS:** Caucasian [odds ratio [OR], 1.65], male [OR, 1.57], and younger (aged 40-64 years compared with 18-39 years: OR, 0.75) members had greater odds of being diagnosed with an OUD. Members with an SDOH vulnerability had 26% higher odds than those without a documented issue. From a prescribing perspective, we found that having an opioid dose of 120 morphine milligram equivalents and contiguous 5-day supply increased odds of OUD by 1.87 times, and an opioid supply of 30 days or longer increased the odds of OUD by 1.56 times.

**CONCLUSIONS:** We built the necessary machine learning infrastructure to identify members with greater than 50% probability of developing OUD. The generated list strategically informs and guides person-centered care and interventions. Through application of these results, we strive to proactively reduce OUD-related structural barriers and prevent OUD from occurring.

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predict a stratified probability of overdose in Medicare populations.<sup>13</sup> This capability of machine learning allows us to strategically target members who have greater than 50% odds of developing an OUD; this helps us, as an MCO, focus resources and proactively intervene with members before OUD diagnosis. We acknowledged that our decision to utilize a generous probability threshold could affect model sensitivity. However, we believed that the use of such a threshold is the surest approach to reduce incidence of OUD and other related adverse events.

Our goals in this paper were (1) to develop and validate a generalizable predictive model identifying the primary risk factors and predictors of OUD in our multistate adult Medicaid population and (2) to calculate probability of OUD diagnosis, creating an actionable list for holistic, person-centered outreach to avoid OUD occurrence.

## METHODS

### Design and Sample

We used our Medicaid enrollment, medical, pharmacy, and care management administrative data from January 1, 2016, to December 31, 2018. We included data from the District of Columbia, Florida, Louisiana, Michigan, Pennsylvania, and South Carolina in a staged study design to develop and test the predictive accuracy of our model, as displayed in **Figure 1**.

For the training model, we used complete 2016 data to predict OUD in 2017 (n = 320,040). We validated predictors through application of the training model to 2017 data, predicting OUD in 2018 (n = 374,809). Finally, we applied our finalized model to 2018 data to predict future OUD in 2019, called the scoring model (n = 589,423). We limited the study population to all continuously enrolled adults to increase likelihood of observing all OUD-related diagnoses within each cohort.

### Outcome Variable: OUD

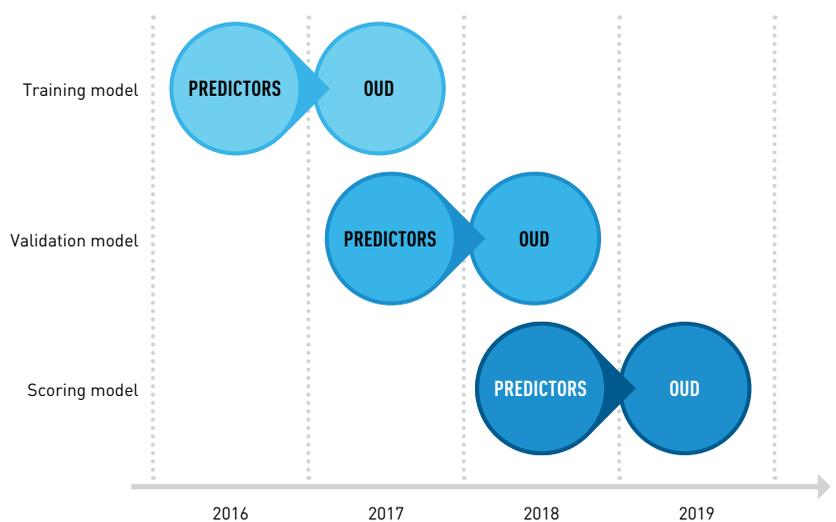
We identified OUD by applying the National Committee for Quality Assurance’s Healthcare Effectiveness Data and Information Set (HEDIS) criteria. HEDIS is a nationally recognized set of quality, access, process, and outcome metrics used to evaluate MCOs’ performance. We used the metric “Initiation and Engagement of Alcohol and Other Drug Abuse or Dependence Treatment (IET)” to focus on OUD-related treatment indicated by an *International Classification of Diseases, Tenth Revision* diagnosis code beginning with F11 (opioid-related disorders). Specific criteria for outcome

## TAKEAWAY POINTS

A Medicaid managed care organization (MCO) developed a machine learning model to identify opioid use disorder (OUD) risk factors and predict OUD incidence in its multistate population.

- ▶ Medicaid beneficiaries are disproportionately affected by OUD, and we found that members experiencing greater social and economic hardships are at even further risk.
- ▶ The application of predictive analytics allows MCOs to proactively intervene and engage at-risk members, potentially preventing incidence or minimizing adverse impacts.
- ▶ To align with new methods of risk identification, we must focus innovative person-centered outreach on the mitigation of modifiable risk factors identified in analyses.

**FIGURE 1.** Machine Learning Design and Time Frame



OUD, opioid use disorder.

identification included an opioid use and dependence diagnosis during any of the following events: (1) an emergency department (ED) visit; (2) an inpatient (IP) discharge; (3) a telephone visit; (4) an online assessment; (5) a detoxification visit; or (6) an outpatient, ED, or IP visit with IET stand-alone visit, IET Visits Group 1 with IET Place of Service Group 1, or IET Visits Group 2 with Place of Service Group 2. IET stand-alone visit and IET Visits groups 1 and 2 contain different revenue codes, Current Procedural Technology codes, and Healthcare Common Procedure Coding System codes.<sup>14</sup>

### Predictor Candidates

As part of our daily operations, we utilize a curated list of patient-level characteristics to predict the likelihood of adverse outcomes and unexpected events. We capture member age, gender, race, language, and aid category from the enrollment data. We apply the Johns Hopkins ACG Care Analyzer data analytics system to medical and pharmacy claims data to create disease indicators for a multitude of physical and behavioral health conditions. To supplement the

**TABLE 1.** Prediction Performance Metrics of the Machine Learning Training and Validation Models

Model description	Training: misclassification rate	Validation: misclassification rate	Training: ROC index	Validation: ROC index
HP random forest	0.018	0.018	0.937	0.917
HP support vector machines	0.019	0.019	0.904	0.905
Neural network	0.018	0.018	0.918	0.918
Decision tree	0.018	0.018	0.704	0.731
Logistic regression	0.019	0.019	0.914	0.915

HP, high-performance; ROC, receiver operating characteristic.

**TABLE 2.** Classification at Different Cutoff Predicted Probabilities in Training and Validation Cohorts

Predicted probability	Training					Validation				
	Sensitivity	Specificity	False positive	False negative	Correct rate	Sensitivity	Specificity	False positive	False negative	Correct rate
5%	62.0%	95.9%	76.7%	0.8%	95.3%	61.5%	96.5%	72.5%	0.8%	95.8%
10%	50.9%	98.2%	64.1%	1.0%	97.3%	52.7%	98.4%	58.3%	1.0%	97.5%
20%	40.4%	99.1%	53.5%	1.2%	97.9%	45.4%	99.1%	48.1%	1.2%	98.0%
30%	33.8%	99.4%	48.2%	1.3%	98.1%	40.0%	99.3%	43.2%	1.3%	98.1%
40%	28.3%	99.5%	45.1%	1.4%	98.1%	33.8%	99.5%	40.2%	1.4%	98.1%
50%	23.8%	99.7%	41.4%	1.5%	98.2%	28.3%	99.6%	38.0%	1.5%	98.1%
60%	18.7%	99.8%	38.3%	1.6%	98.2%	22.6%	99.7%	36.0%	1.6%	98.1%
70%	13.6%	99.8%	35.7%	1.7%	98.2%	16.8%	99.8%	33.6%	1.8%	98.1%
80%	7.6%	99.9%	32.7%	1.8%	98.1%	10.1%	99.9%	31.4%	1.9%	98.0%
90%	1.6%	100.0%	25.8%	1.9%	98.1%	2.3%	100.0%	24.1%	2.1%	97.9%

demographic and clinical information, we include an indicator for social determinants of health (SDOH) vulnerability as reported by members via care management outreach. If a member indicates any issues with housing, food, clothing, transportation, education, utilities and/or literacy, they are deemed to have an SDOH vulnerability.

To enhance applicability to our specific outcome variable for this study, we included a series of variables related to opioid prescriptions. We identified opioid prescriptions using the Medi-Span National Drug Codes for Analgesics–Opioid. Variables included an indicator of any opioid prescription, total number of pain medication prescriptions, daily morphine milligram equivalent (MME) dosing of greater than 120 MME for 5 contiguous days, and short-acting or long-acting opioid. Long-acting opioids include naturally long-acting versions and extended-release formulations. We added predictor candidates for the number of prescribers of opioids, number of pharmacies, and an indicator of high-risk utilization; this indicator was defined as 1 or more visits to a mental health specialist, 1 or more mental health IP admissions, or 1 or more ED visits in the observation year. We also captured alcohol, opioid, and other substance use disorder in the baseline year for each cohort.

Due to the skewed distribution of included continuous predictor candidates, we decided to create categorical variables where possible. We reviewed the distribution of each continuous variable and collapsed the data to create evenly distributed categories.

### Statistical Analyses

Using our staged approach, we began developing and predicting algorithms using a series of machine learning approaches in our training model, including multivariate logistic regression, decision trees, random forest, neural networks, support vector machine, and other high-performing data mining. We compared the receiver operating characteristic (ROC) curve index, misclassification rate, and interpretability to select the best model and use it for record scoring.

In **Table 1**, we display the prediction performance metrics of the training and validation models. The misclassification rate was less than 0.019 for all algorithms. The ROC index remained high across the fitted algorithms (> 0.904) except the decision tree model, which was automatically generated. Due to the similar prediction performance, we decided to use the multivariate logistic regression (validation C statistic = 0.914; misclassification = 0.019) to identify predictors of OUD risk. The selected model allowed for the interpretation of each risk factor’s magnitude. At a 50% predicted probability, the multivariate logistic regression validation model yielded a sensitivity of 28.3%, a specificity of 99.6%, and a false-positive rate of 38.0% (**Table 2**).

After selecting the logistic regression model, we applied a backward elimination method, an approach that eliminates the least significant variables to create a high-performing, parsimonious model (**eAppendix Table 1** [eAppendix available at [ajmc.com](#)]).

We reviewed the remaining variables for clinical and industry relevance to OUD diagnosis. The removed predictor candidates included several chronic condition indicators, the number of opioid prescribers, and the number of pharmacies filling opioid prescriptions. The remaining variables are presented in **Table 3**. All analyses were conducted using SAS EG 7.1 and SAS EM 14.1 (SAS Institute). A P value less than .05 was deemed statistically significant.

## RESULTS

### Patient Characteristics

Our training cohort had more women (64.0%), adults 40 years and older (48.8%), African Americans (41.7%), and English speakers (85.9%) than the scoring cohort (61.8%, 45.8%, 36.6%, and 76.4%, respectively). Disease prevalence was higher in our training cohort than our scoring cohort across all included conditions. Prior alcohol use disorder and other substance use disorder were consistent across the 3 cohorts, whereas prior OUD increased in prevalence from the training (1.7%) to scoring (2.4%) cohorts. In the training model, 6269 members developed an OUD in 2017 (2.0%), which remained constant in 2018 (2.1%). Results are displayed in Table 3.

### Factors Associated With Risk of OUD

Using multivariate logistic regression (**Figure 2**), we found that Caucasians (odds ratio [OR], 1.65; 95% CI, 1.53-1.77), men (OR, 1.57; 95% CI, 1.48-1.67), and those younger than 40 years (aged 40-64 years compared with 18-39 years: OR, 0.75; 95% CI, 0.67-0.85; ≥65 years compared with 18-39 years: OR, 0.56; 95% CI, 0.42-0.75) had greater odds of being diagnosed with an OUD. Members who do not qualify for Medicaid through Social Security Income (SSI) benefits had 12% higher odds of having OUD than those with SSI (95% CI, 1.05-1.20), and members with an SDOH vulnerability had 26% higher odds of having an OUD than those without a documented SDOH issue (95% CI, 1.13-1.40). Clinically, diagnoses of bipolar disorder (OR, 1.39; 95% CI, 1.27-1.51), depression (OR, 1.82; 95% CI, 1.69-1.97), seizures (OR, 1.28; 95% CI, 1.20-1.37), anxiety (OR, 1.49; 95% CI, 1.49-1.60), sickle cell disease (OR, 1.69; 95% CI, 1.14-2.48), and HIV (OR, 1.58; 95% CI, 1.35-1.85) were associated with greater odds of having an OUD.

We found that members with documented tobacco use (OR, 2.68; 95% CI, 2.51-2.86), prior substance use disorder (OR, 1.69; 95% CI, 1.54-1.85), or prior OUD (OR, 17.79; 95% CI, 16.50-19.18) had greater

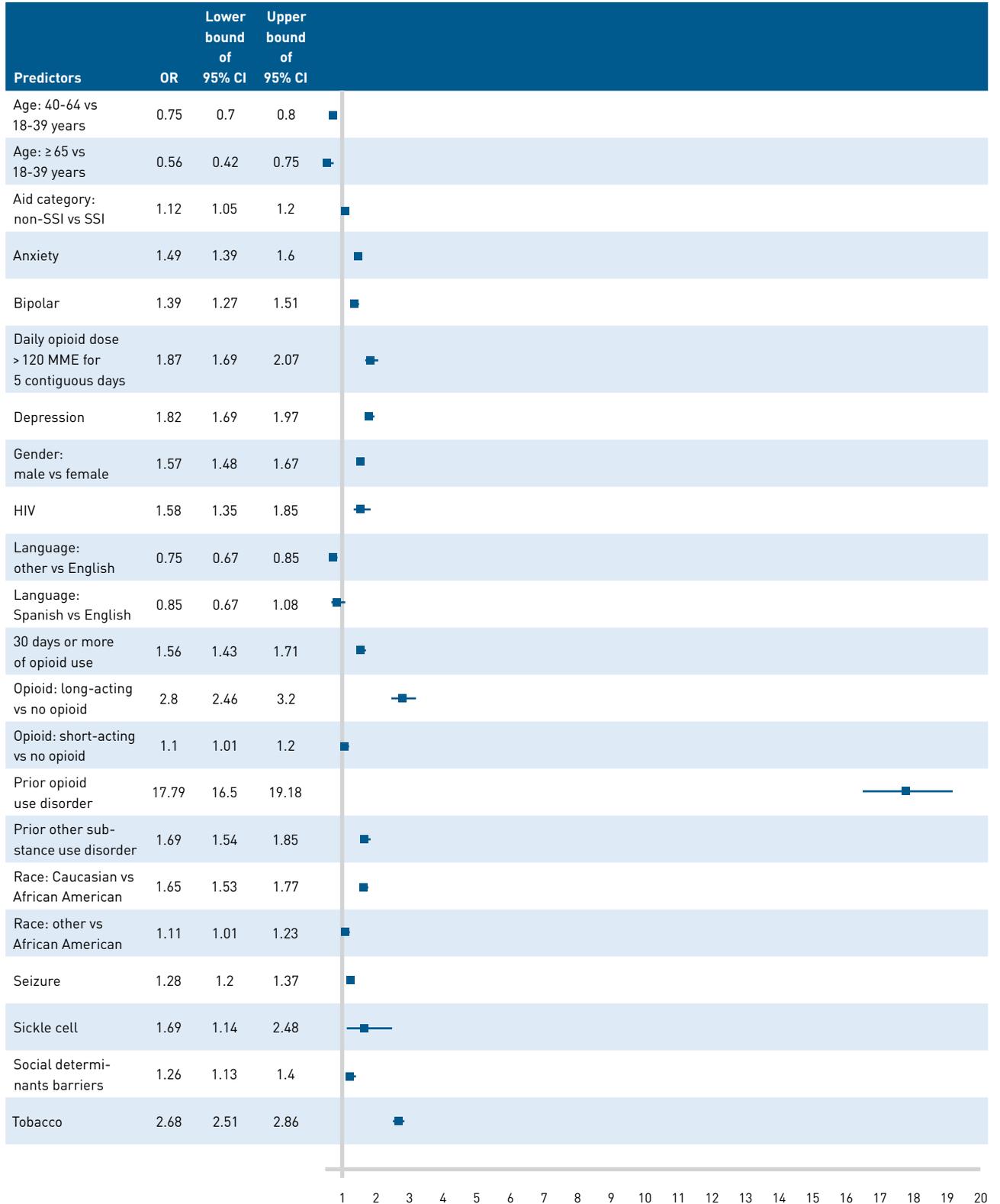
**TABLE 3.** Patient Characteristics in Each Machine Learning Cohort

Variables	Category	Training cohort (2016, predicting 2017)		Validation cohort (2017, predicting 2018)		Scoring cohort (2018, predicting 2019)	
		n	%	n	%	n	%
Total		320,040		374,809		589,423	
Gender	Female	204,971	64.0	236,149	63.0	364,102	61.8
	Male	115,069	36.0	138,660	37.0	225,321	38.2
Age in years	18-39	164,042	51.3	194,526	51.9	319,130	54.1
	40-64	139,725	43.7	164,027	43.8	241,923	41.0
	≥ 65	16,273	5.1	16,256	4.3	28,370	4.8
Language	English	274,821	85.9	306,992	81.9	450,156	76.4
	Spanish	12,035	3.8	12,273	3.3	20,110	3.4
	Other	33,184	10.4	55,544	14.8	119,157	20.2
Race	African American	133,487	41.7	152,470	40.7	215,976	36.6
	Caucasian	116,230	36.3	137,844	36.8	214,546	36.4
	Other	70,323	22.0	84,495	22.5	158,901	27.0
Aid category	Non-SSI	82,775	25.9	80,243	21.4	97,733	16.6
	SSI	237,265	74.1	294,566	78.6	491,690	83.4
SDOH barriers	No	307,042	95.9	358,183	95.6	563,809	95.7
	Yes	12,998	4.1	16,626	4.4	25,614	4.3
Bipolar disorder		15,658	4.9	17,659	4.7	24,740	4.2
Depression		113,132	35.3	129,417	34.5	185,366	31.4
Anxiety		72,633	22.7	85,198	22.7	124,126	21.1
HIV		6078	1.9	6716	1.8	9375	1.6
Seizure		79,518	24.8	89,527	23.9	122,108	20.7
Sickle cell		534	0.2	491	0.1	581	0.1
Tobacco use		90,891	28.4	10,7915	28.8	161,156	27.3
Daily opioid dose > 120 MME for 5 contiguous days		14,206	4.4	10,070	2.7	13,139	2.2
30 days or more of opioid use		45,300	14.2	42,615	11.4	45,730	7.8
Opioid type	Long-acting	10,041	3.1	10,047	2.7	13,935	2.4
	Short-acting	97,740	30.5	99,561	26.6	111,765	19.0
	No opioid	212,259	66.3	265,201	70.8	463,723	78.7
Prior alcohol use disorder		7758	2.4	9229	2.5	14,093	2.4
Prior opioid use disorder		5432	1.7	7138	1.9	14,212	2.4
Prior other substance use disorder		9358	2.9	11,256	3.0	17,931	3.0
Outcome variable: current opioid use disorder		6269	2.0	7867	2.1	Predicted outcome	

MME, morphine milligram equivalent; SDOH, social determinants of health; SSI, Social Security Income.

odds of an OUD diagnosis than members without those traits. In regard to prescribing behavior, we found that having an opioid dose greater than 120 MME for 5 contiguous days increased odds of OUD by 1.87 times (95% CI, 1.69-2.07) and that a 30-day or longer supply of opioids increased the odds by 1.56 times (95% CI, 1.43-1.71). Prescriptions for long-acting opioids and short-acting opioids also increased the odds of a member developing an OUD by 2.8 (95% CI, 2.46-3.20) and 1.1 (95% CI, 1.01-1.20) times, respectively, compared with not having an opioid prescription.

**FIGURE 2.** Adjusted ORs and 95% CIs Displayed From Training Model to Predict 2017 Opioid Use Disorder



MME, morphine milligram equivalent; OR, odds ratio; SSI, Social Security Income.

Using our model to score the 2018 cohort, we identified 6210 members (1.05%) with higher than a 50% predicted probability of an OUD diagnosis in 2019. All predicted probability categories and count of identified members can be found in [eAppendix Table 2](#).

## DISCUSSION

This study highlights key demographic, clinical, and prescribing predictors of OUD in an adult Medicaid population. We used administrative claims data to develop machine learning models, selecting logistic regression as our statistical approach due to its high ROC index, low misclassification rate, and ease of interpretability. Overall, we found that male members, those younger than 40 years, and those with a behavioral health diagnosis, HIV, or a history of various substance use disorders (tobacco, opioid, or other substances) had increased odds of developing an OUD. Related to care delivery, negative prescribing patterns were also associated with OUD diagnosis. These results align with previously conducted studies of commercial and general populations and other national statistics on those affected by the opioid epidemic.<sup>5,9-12,15</sup>

Specific to our Medicaid population, we found that individuals eligible for Medicaid due to income alone are more likely to have OUD than those eligible for SSI benefits (aged, disabled, and/or blind). SDOH vulnerability was also a strong predictor of OUD. Medicaid beneficiaries are disproportionately affected by OUD, and this finding indicates that those members experiencing greater social and economic hardships are at even further risk. Our results parallel those of a recent study, which showed that areas experiencing a major economic downturn observed an increase in opioid-related deaths.<sup>16</sup> As a Medicaid MCO, our approach cannot simply focus on clinical need and utilization. Rather, we have to continue to address the structural barriers affecting quality of life and overall well-being through holistic, person-centered solutions and health and social service provider–payer collaboration.

As we begin to incorporate predictive analytics in our care management strategy, it is imperative that specific consideration be paid to how the outreach conversations are conducted. Because the identified members have not yet been diagnosed with an OUD, and due to the overall sensitive nature of the condition, the focus should not be on the management of disease. We need to focus on the modifiable risk factors as identified in this study, such as tobacco use, opioid prescription use, and SDOH vulnerability. Our goal is to provide our care managers with actionable ways to help build the member's capacity for healthier behaviors and lifestyles. For example, by providing smoking cessation support, we can introduce skills for managing addiction and eliminate a negative habit. The proactive outreach will help us to manage risk factors that may predispose a member to an OUD. It also builds the relationship of trust and support necessary for effective care management in the future.

Although our model specificity is high, the sensitivity of the model is low as a result of the low prevalence of OUD in our population. As an MCO interested in avoiding adverse outcomes,

we are strategically overincluding members with a probability of developing OUD greater than 50% on our outreach list and accurately excluding those with extremely low risk of OUD incidence. By using this conservative probability estimate, we believe we are best able to proactively engage members to prevent OUD from ever occurring. We also decided to include prior OUD as a covariate in our model in order to catch all members and address the realities of practice. The Medicaid population has high need and high demand on their time, which can make it difficult to maintain engagement in care management programs. The inclusion of individuals with a prior OUD diagnosis in our analysis provides another opportunity for engagement. We can cross-check the list of members generated through this model to those actively working with a care manager to focus efforts on nonengaged members.

Additionally, we recognize that care is local, and program structure and prior authorization policies vary across states. We work closely with all our state partners to improve appropriate utilization, collaborate with community organizations, and introduce auxiliary services as needed. Our care managers often come from the same community as the members they are serving. This provides an invaluable asset to our organization in connecting members with local resources and programs. We intend to work with our state partners to continue to support a comprehensive and person-centered approach to OUD.

Our organizational response to the opioid epidemic provided the catalyst to examine the integration of predictive analytics into care management processes, which traditionally focus outreach on the members at highest risk. We are currently advancing our analytic capabilities and evaluating how data are informing our person-centered approach, and we will be applying the list to future member engagement strategies. This study helped to build the necessary infrastructure to create a manageable list for outreach. The approach can be replicated for other adverse events and generate actionable lists for intervention.

As we integrate the results into our workflow, we will continue to refine our machine learning models to improve predictive accuracy and to indicate which members experience significant increases in probability of OUD development. Results will inform and modify future person-centered outreach strategies.

### Limitations

We were limited by our use of administrative claims data, which allowed us to only measure the impact of observable characteristics and view the outcome among members receiving care. Next, we utilized data from an entire observation year to predict a member's probability of OUD in the following year. This created variation in the window of time from observation to diagnosis of OUD, weakening the link between specific predictor variables and the outcome. Additionally, OUD prevalence in our population is low, which has resulted in an elevated false-positive rate. We believe that with more data over time, we will be able to refine the model and correct that issue.

We assumed that the disease indicators generated in the Johns Hopkins ACG Care Analyzer data are lifelong conditions. Similarly, we chose to include an indicator for SDOH collected during outreach by a care manager, resulting in a large number of missing values. We combined missing and “none identified,” underreporting SDOH issues among our membership.

In the development of the models, we chose to ignore interactions and focus on main effects to ease data interpretation. We removed some chronic conditions common in the Medicaid population (eg, diabetes, asthma) from our final model, which did not affect model robustness. The inclusion of line of business indicators as proxies for state-level effects only slightly increased the model performance ( $C = 0.917$ ) and did not affect the ORs (eAppendix Table 3). Because of this, we chose to exclude state-level proxies. We also opted to use internally collected person-level SDOH data opposed to state-level socioeconomic data due to our person-centered unit of analysis and our sole focus on the Medicaid population, whose unique experiences and vulnerabilities are better captured through personal outreach. Finally, we conducted some sensitivity analyses in which prior OUD diagnosis was removed (eAppendix Table 4). The model's significant predictors and performance remained similar.

## CONCLUSIONS

As states, health plans, and providers collaborate to reduce the impact of OUD on communities, it is critical to effectively target and deploy resources. We decided to more proactively address the physical, behavioral, and social risk factors associated with the development of OUD. Through machine learning methodologies, we generated predicted probabilities of OUD among our members, creating a concise list of members with greater than a 50% probability of developing OUD over the next year. We will use this list to inform strategic person-centered outreach and enhance our internal efficiency. ■

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eAppendix.

eAppendix Table 1. Model without backward selection

<b>Odds Ratio Estimates</b>			
<b>Effect</b>	<b>Point Estimate</b>	<b>95% Wald Confidence Limits</b>	
Daily opioid 120 MME and contiguous five days	1.870	1.689	2.071
More than 30 days of opioid use	1.560	1.425	1.709
Prior alcohol use disorder	0.925	0.812	1.052
Prior opioid use disorder	17.840	16.545	19.236
Prior other substance use disorder	1.704	1.551	1.873
Bipolar disorder	1.381	1.263	1.510
Depression	1.822	1.690	1.966
HIV	1.584	1.354	1.854
Schizophrenia	1.044	0.918	1.187
Seizure	1.285	1.201	1.374
Anxiety	1.490	1.392	1.595
Sickle cell	1.684	1.143	2.481
Tobacco use	2.680	2.511	2.861
Male vs Female	1.573	1.478	1.675
age:40-64 vs 18-39	0.747	0.700	0.797
age:65+ vs 18-39	0.556	0.414	0.746
Spanish vs English	0.846	0.666	1.075
Other language vs English	0.751	0.666	0.848
Caucasian vs African American	1.650	1.535	1.774
Other race vs African American	1.112	1.008	1.226
Non-SSI vs SSI	1.122	1.049	1.200
SDoH barriers	1.259	1.129	1.404
Opioid long acting vs no opioid	2.807	2.462	3.200
Opioid short acting vs no opioid	1.103	1.012	1.202

C=0.914

**eAppendix Table 2. Predicted probability of experiencing opioid use disorder in 2019 in the scoring cohort**

Predicted probability	No. of members	Percent	Cumulative No. of members	Cumulative percent
90%+	439	0.07	439	0.07
80% – 90%	1,584	0.27	2,023	0.34
70% – 80%	1,457	0.25	3,480	0.59
60% – 70%	1,305	0.22	4,785	0.81
50% – 60%	1,425	0.24	6,210	1.05
40% – 50%	1,667	0.28	7,877	1.34
30% – 40%	1,953	0.33	9,830	1.67
20% – 30%	2,257	0.38	12,087	2.05
10% – 20%	4,294	0.73	16,381	2.78
< 10%	573,042	97.22	589,423	100

**eAppendix Table 3. Sensitivity Test: Inclusion of line of business (LOB)-indicator as a covariate**

<b>Odds Ratio Estimates</b>			
<b>Effect</b>	<b>Point Estimate</b>	<b>95% Wald Confidence Limits</b>	
		Daily opioid 120 MME and contiguous five days	1.912
More than 30 days of opioid use	1.591	1.452	1.743
Prior opioid use disorder	17.223	15.973	18.571
Prior other substance use disorder	1.721	1.569	1.888
Bipolar disorder	1.421	1.302	1.551
Depression	1.804	1.672	1.946
HIV	1.47	1.255	1.723
Seizure	1.287	1.203	1.377
Anxiety	1.514	1.414	1.62
Sickle cell	1.962	1.336	2.882
Tobacco use	2.695	2.524	2.877
Male vs Female	1.512	1.421	1.609
age:40-64 vs 18-39	0.752	0.704	0.802
age:65+ vs 18-39	0.7	0.519	0.943
Spanish vs English	0.804	0.632	1.022
Other language vs English	0.244	0.155	0.383
Caucasian vs African American	1.847	1.708	1.997
Other race vs African American	1.419	1.28	1.574
Non-SSI vs SSI	1.217	1.133	1.308
SDoH barriers	1.304	1.168	1.456
Opioid long acting vs no opioid	2.593	2.268	2.965
Opioid short acting vs no opioid	1.134	1.04	1.236
LOB 2 vs 1	0.578	0.53	0.63
LOB 3 vs 1	0.503	0.446	0.567
LOB 4 vs 1	0.53	0.476	0.59
LOB 5 vs 1	2.463	1.544	3.93
LOB 6 vs 1	0.787	0.683	0.907
LOB 7 vs 1	0.533	0.476	0.596

C=0.917

**eAppendix Table 4. Sensitivity Test: Exclusion of prior OUD as covariate**

<b>Odds Ratio Estimates</b>			
<b>Effect</b>	<b>Point Estimate</b>	<b>95% Wald Confidence Limits</b>	
		Daily opioid 120 MME and contiguous five days	2.22
More than 30 days of opioid use	1.548	1.42	1.687
Prior alcohol use disorder	1.128	1.005	1.265
Prior other substance use disorder	3.505	3.235	3.798
Bipolar disorder	1.448	1.338	1.568
Depression	1.983	1.847	2.129
HIV	1.494	1.294	1.725
Seizure	1.274	1.197	1.356
Anxiety	1.452	1.363	1.546
Tobacco use	2.784	2.619	2.961
Male vs Female	1.611	1.521	1.707
age:40-64 vs 18-39	0.712	0.67	0.755
age:65+ vs 18-39	0.498	0.372	0.667
Spanish vs English	0.864	0.69	1.082
Other language vs English	0.746	0.665	0.837
Caucasian vs African American	1.741	1.628	1.862
Other race vs African American	1.123	1.025	1.231
Non-SSI vs SSI	1.148	1.079	1.222
SDoH barriers	1.272	1.152	1.406
Opioid long acting vs no opioid	5.111	4.532	5.764
Opioid short acting vs no opioid	1.168	1.077	1.267

C=0.89