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Using Real-World Evidence to Affect the Opioid Crisis

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ABSTRACT

The opioid crisis is growing daily. Overreliance on opioids for pain management has led to the worst drug crisis in American history. Of the nearly 64,000 American deaths in 2016 due to drug overdoses, nearly two-thirds (66%) involved a prescription or illicit opioid.

Over 100,000 deidentified, state-level patient claims records were analyzed to assess the likelihood of an opioid complication after receiving a prescription for opioids.

Descriptive statistics were reported on all variables and binary logistic regression was used to determine the likelihood of opioid complications in patients prescribed at least one opioid adjusting for age, gender, race, and behavioral health diagnosis. Adjusted odd ratios with 95% confidence interval were reported.

Our study showed that patients who have a behavioral health diagnosis are almost 55 times more likely to have an opioid complication if prescribed opioids than patients without such a diagnosis. (OR=54.79 CI [16.50,339.14])

Electronic medical records should identify patients who had a previous behavioral health diagnosis to receive alternative therapies to opioids for pain management. Intervention at this patient level is crucial to stemming the opioid crisis in potentially vulnerable patient cohorts.

INTRODUCTION

The opioid crisis is growing daily. Overreliance on opioids for pain management has led to the worst drug crisis in American history. Of the nearly 64,000 American deaths in 2016 due to drug overdoses, nearly two-thirds (66%) involved a prescription or illicit opioid. The CDC estimates the total economic burden of prescription opioid misuse in the US is $78.5 billion a year, including the costs of health care, lost productivity, addiction treatment, and criminal justice involvement.

Prevention and access to treatment for opioid addiction and overdose reversal drugs are critical to fighting this epidemic. Primary care settings have increasingly become a gateway to better care for individuals with both behavioral health (including substance use) and primary care needs.

To prevent new opioid use disorder cases, The Center for Drug Evaluation and Research has approved ongoing expansion of opioid Risk Evaluation and Mitigation Strategies and education about appropriate pain management. They are evaluating benefits and risks of currently approved opioids and additional methods to improve prescribing practices.

This study illustrates the value and insight that can be gained by utilizing Real-World Evidence in the fight against the opioid crisis. Furthermore, it highlights the feasibility and improved time to insight utilizing the SAS® Health Analytics Framework.

METHODS

Over 100,000 deidentified, state-level patient claims records were analyzed to assess the likelihood of an opioid complication after receiving a prescription for opioids.

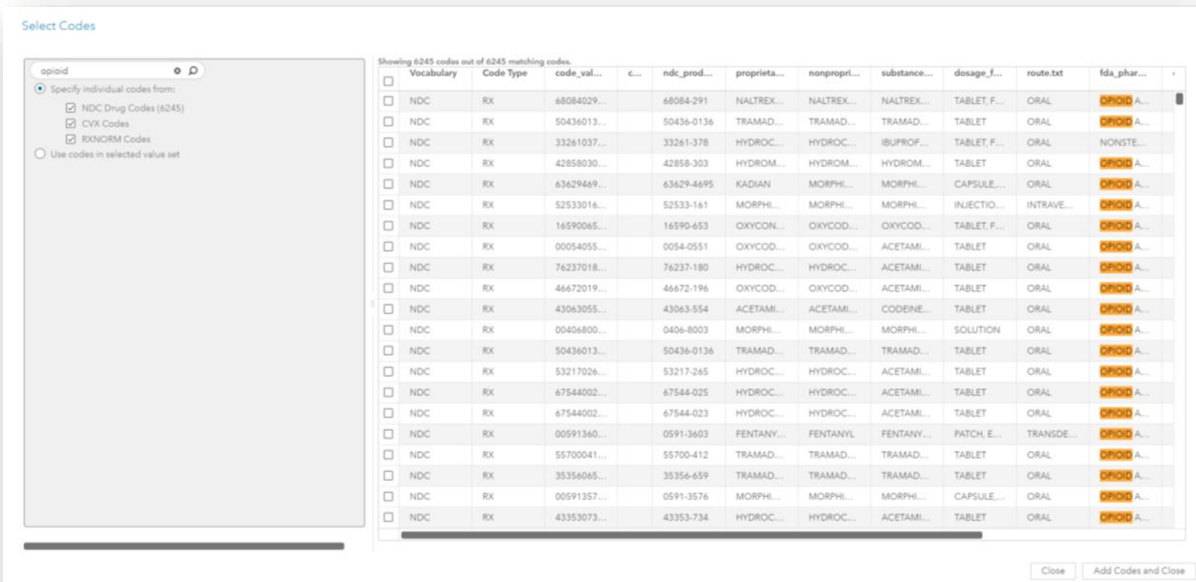
Patient cohorts were defined as any patient who received at least one opioid as defined by the NDC database (n=9,088).

The dependent variable was opioid complications, defined as ICD-10 diagnosis categories of opioid poisoning or opioid abuse or opioid dependence.

Independent variables included previous behavioral health diagnosis, whether a patient was an adolescent between the ages of 12-17, gender, race, and geographic location.

Descriptive statistics were reported on all variables and binary logistic regression was used to determine the likelihood of opioid complications in patients prescribed at least one opioid adjusting for age, gender, race, and behavioral health diagnosis. Adjusted odd ratios with 95% confidence interval were reported. Further predictive modeling used decision tree analysis, Forest plot, neural network. Models were compared using the KS Youden fit statistic. Cohort creation and analyses were performed and visualized using SAS® Health Analytics Framework.

Display 1 is a screen capture illustrating the cohort definitions using keyword search of “Opioid” in Prescription Fills.



Display 1 Expression Builder Interface for SAS Health Analytics Framework -Cohort definition using keyword search.

IDENTIFYING THE TARGET PATIENT POPULATION

Using the SAS® Health Analytics Framework Cohort Builder, we identified patients who had filled a prescription for opioid medication. “Opioid” was the keyword that was used to search for the opioid products of interest. Products in the form of syrup were excluded to minimize patients who received cough medicines that could potentially confuse the results.

BUILDING THE INDEPENDENT VARIABLES FOR THE ANALYTIC DATASET

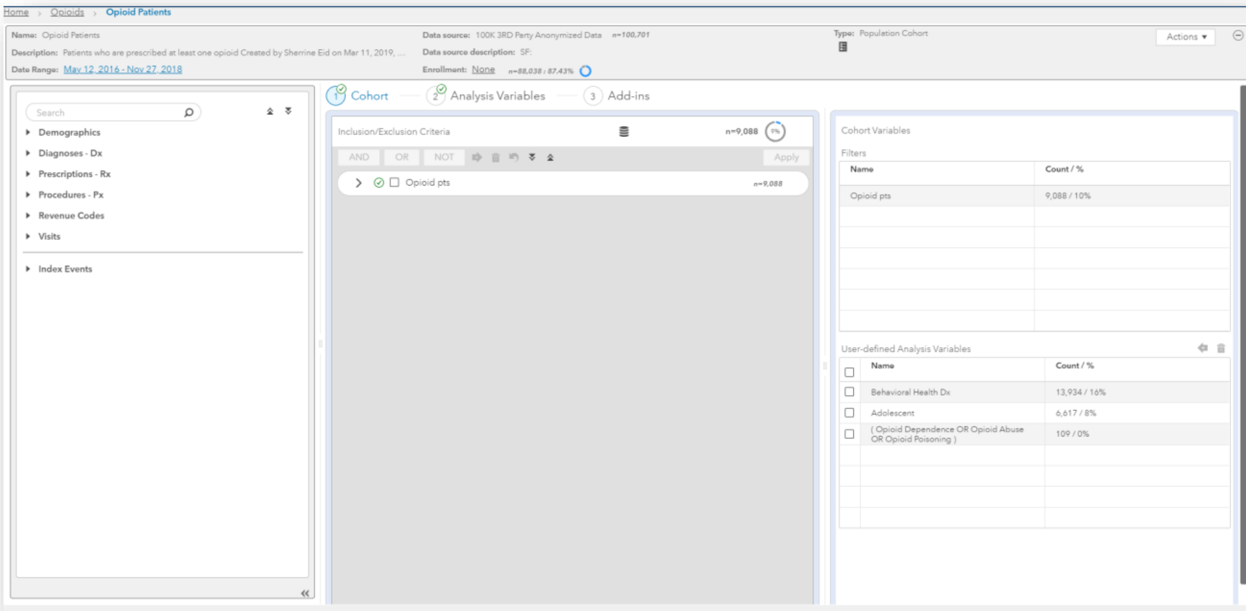
Using the SAS® Health Analytics Framework Cohort Builder, we defined the independent variables, BEHAVORIAL HEALTH and ADOLESCENT, using the User-Defined Analysis Variables expression builder. Behavioral Health Diagnosis was defined as patient who had an ICD-10 diagnosis related to mental illness or behavioral health. Adolescents were defined as patients who were between the ages of 12-17 at the study start.

Predefined variables of RACE, GENDER, ZIPCODE,

BUILDING THE DEPENDENT VARIABLES FOR THE ANALYTIC DATASET

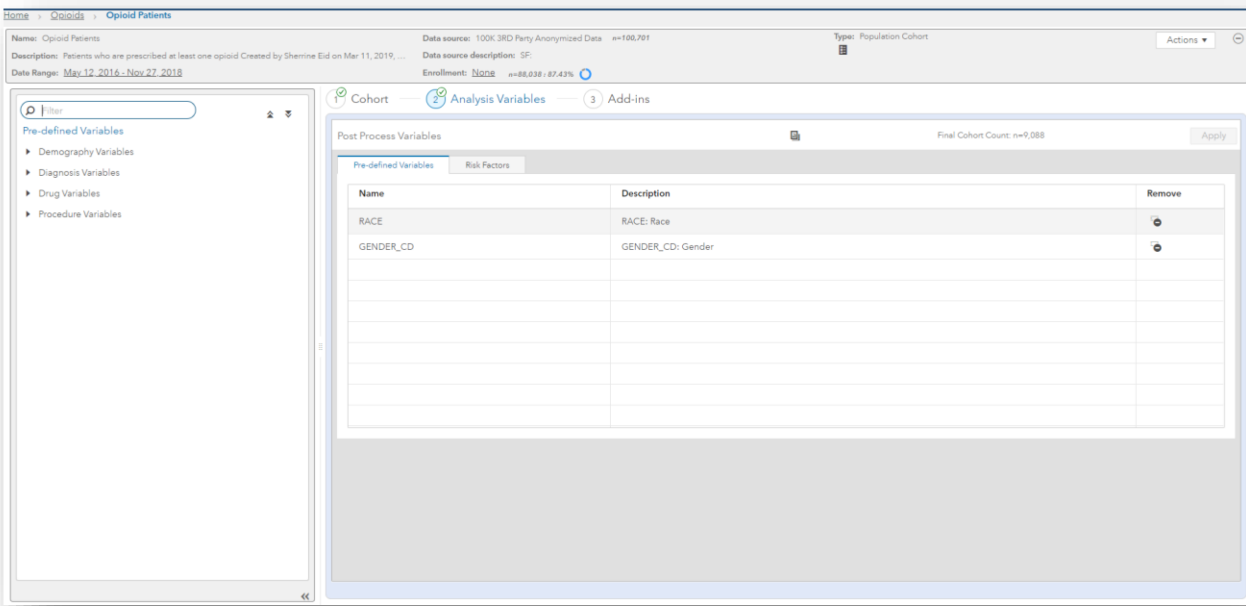
Using the SAS® Health Analytics Framework Cohort Builder, we defined the dependent variables, Opioid Complications, Opioid Abuse, Opioid Dependence and Opioid Poisoning, using the User-Defined Analysis Variables expression builder. Opioid Complications was defined as composite variable of a patient who had an ICD-10 diagnosis of Opioid Abuse OR Opioid Dependence OR Opioid Poisoning.

Display 2 is a screen capture illustrating the final cohort definitions with the User-Defined Analysis variables, Behavioral Health, Adolescent and the Outcome variable of Opioid Complications -defined as Opioid Abuse OR Opioid Dependence OR Opioid Poisoning.



Display 2.Cohort Builder Interface for SAS Health Analytics Framework -Cohort definition and User-Defined Analysis Variables.

Display 3 is a screen capture illustrating the Pre-Defined Analysis variables, RACE and GENDER.



Display 3 Predefined Analysis Variables Interface for SAS Health Analytics Framework

RESULTS

DEMOGRAPHICS

Figure 1. Race and Ethnicity Distribution of Patients Prescribed OpioidsFigure 1 illustrates the race and ethnicity distribution. Over 76% of patients were White, and 16% were Black. Figure 2 illustrates the gender distribution. Over 57% were female and 42.5% were male. Adolescent patients accounted for 6.2% of our sample.

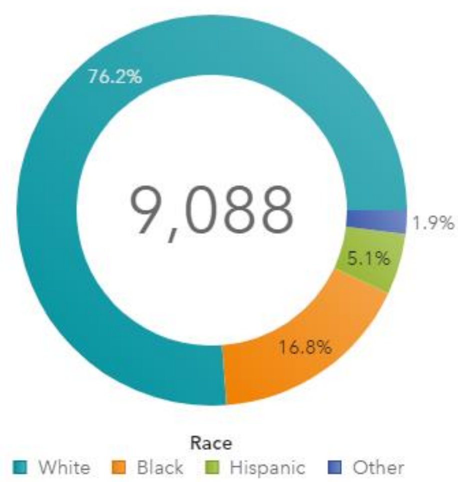


Figure 1. Race and Ethnicity Distribution of Patients Prescribed Opioids

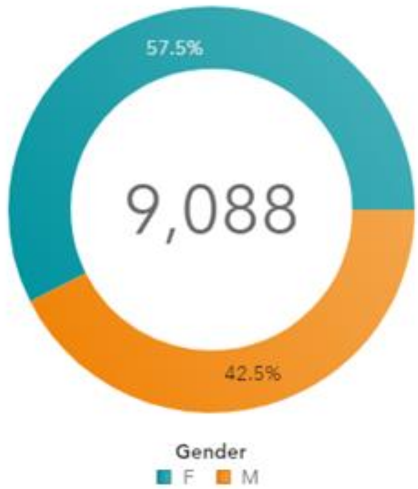


Figure 2 Gender Distribution of Patients Prescribed Opioids

Figure 3 illustrates the distribution of Behavioral Health, Adolescents and Opioid complications in our study.

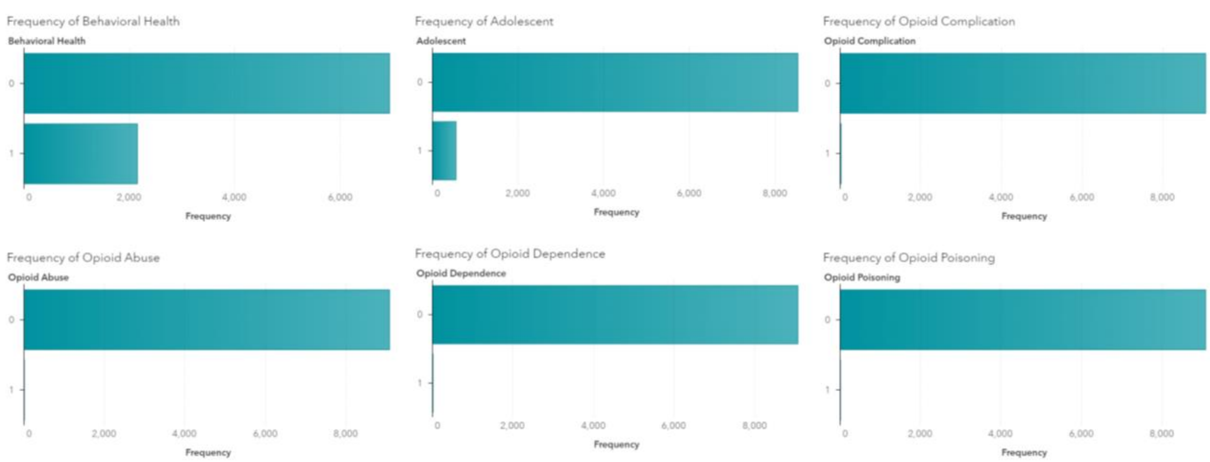


Figure 3 Baseline Characteristics of Patients Prescribed Opioids

Characteristic	Value	No Opioid Complications	Opioid Complications	p-value
Total	Total	N=9053	N=35	
Gender	F	5209 (57.5)	13 (37.1)	5.934 (0.0149)
	M	3844 (42.5)	22 (62.9)	
Race	Black	1520 (16.8)	7 (20.0)	1.858 (0.6025)
	Hispanic	457 (5.0)	3 (8.6)	
	Other	177 (2.0)	0 (0.0)	
	White	6899 (76.2)	25 (71.4)	
Elixhauser Comorbidity Risk Score	ELIX_risk_score	0.358 (2.081)	0.771 (4.426)	-0.552 (0.5842)
Behavioral Health Dx	IV1	0.234 (0.424)	0.943 (0.236)	-17.687 (0.0000)
Adolescent	IV2	0.061 (0.240)	0.114 (0.323)	-0.968 (0.3399)

Table 1 lists the baseline characteristics of patients in our cohort. Thirty-five patients (0.04%) had an opioid complication. Bivariate analyses showed a statistically significant difference between gender and behavioral health diagnosis distributions.

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Table 1. Baseline Characteristics of Patients Prescribed Opioids

PREDICTIVE ANALYTICS

Figure 4 illustrates patients who have a behavioral health diagnosis are almost 55 times more likely to have an opioid complication if prescribed opioids than patients without such a diagnosis. (OR=54.79 CI [16.50,339.14])

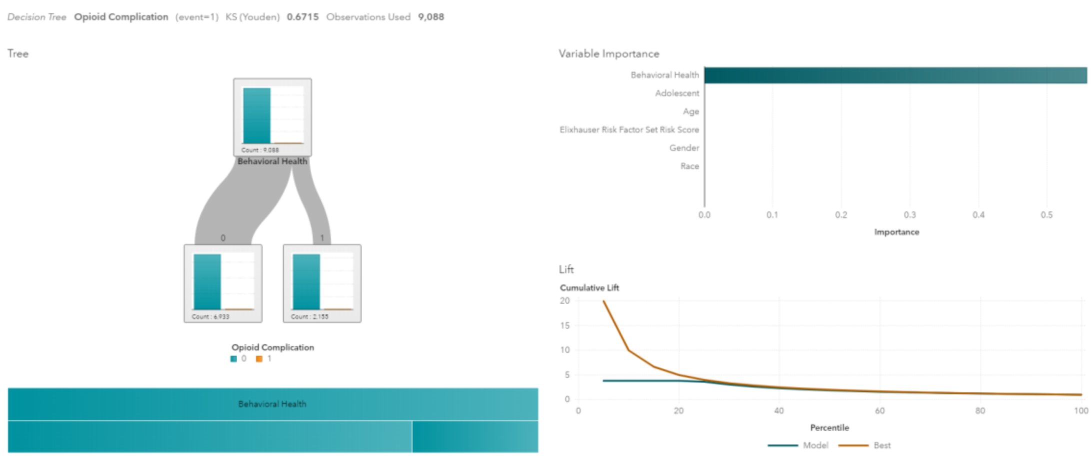

Figure 5 illustrates the decision tree also showed similar results.

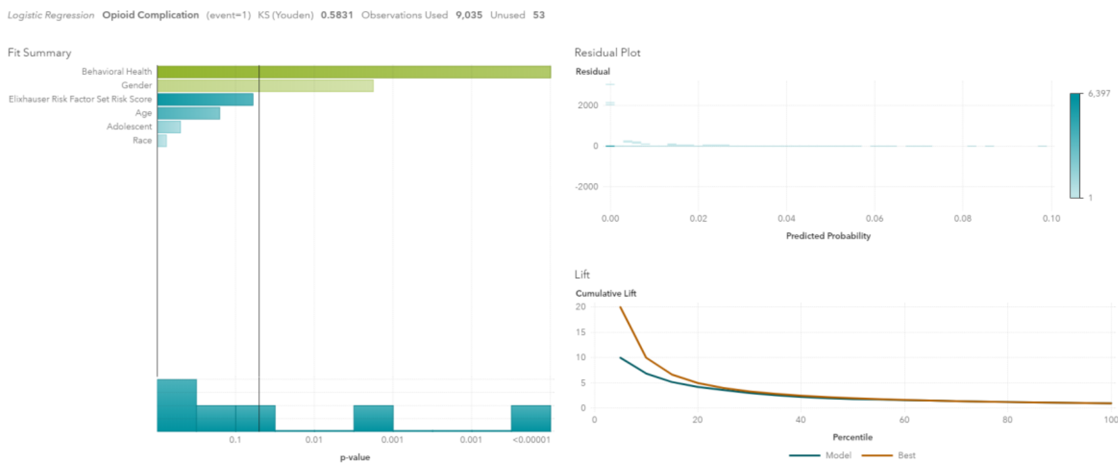

Figure 4 Likelihood of Opioid Complications in Patients Prescribed Opioids

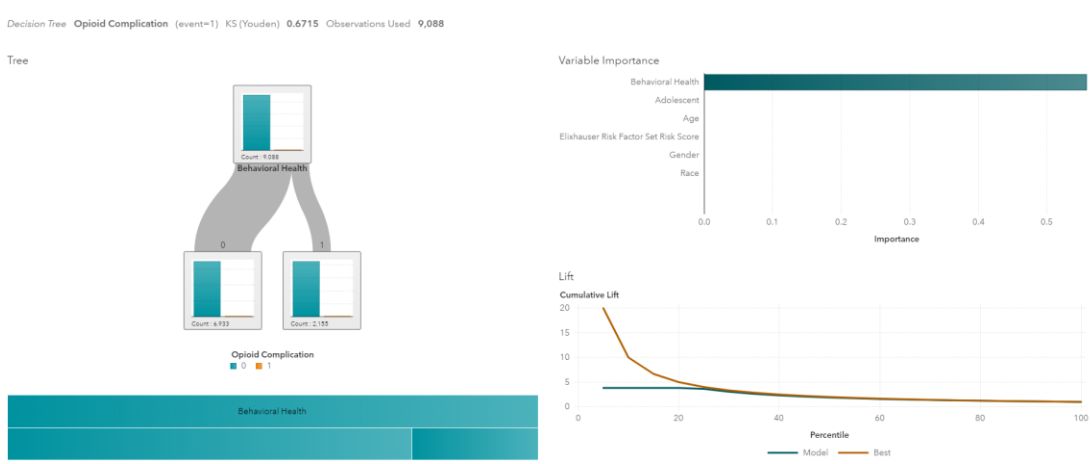

Figure 5 Predicting Opioid Complications using a Decision Tree

MACHINE LEARNING

The logistic regression model and decision tree were duplicated as a Forest plot and neural network. Figure 6 shows the Forest plot. It illustrates that the most important variable was the Elixhauser Comorbidity Risk Score followed by a Behavioral health diagnosis. Furthermore, neural network showed little insight. Figure 7 illustrates the neural network analysis.

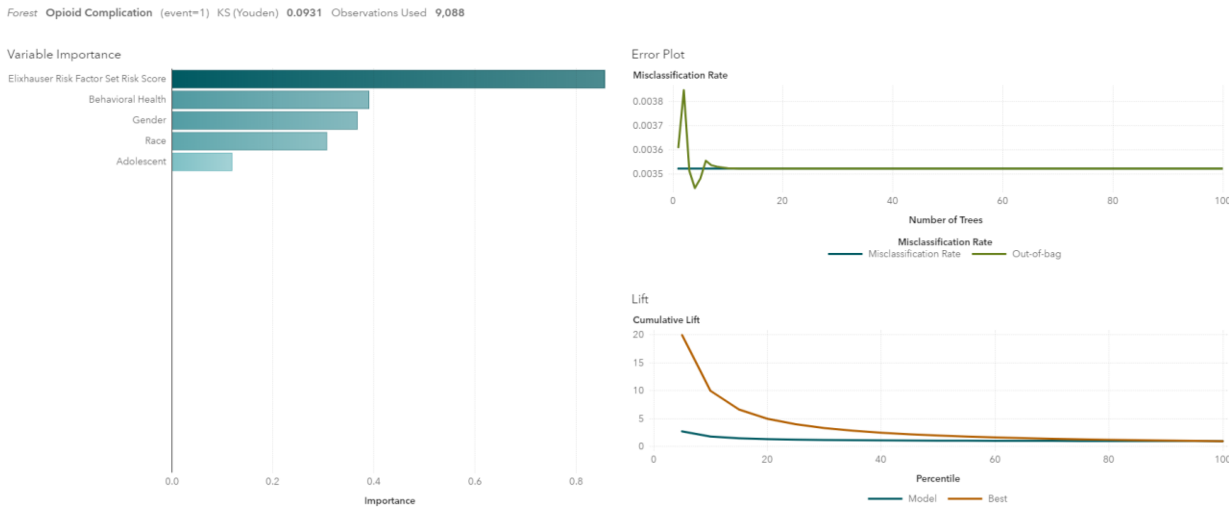

Figure 6 Machine Learning Using Forest Plots to Determine the Variable Importance in Opioid Complications

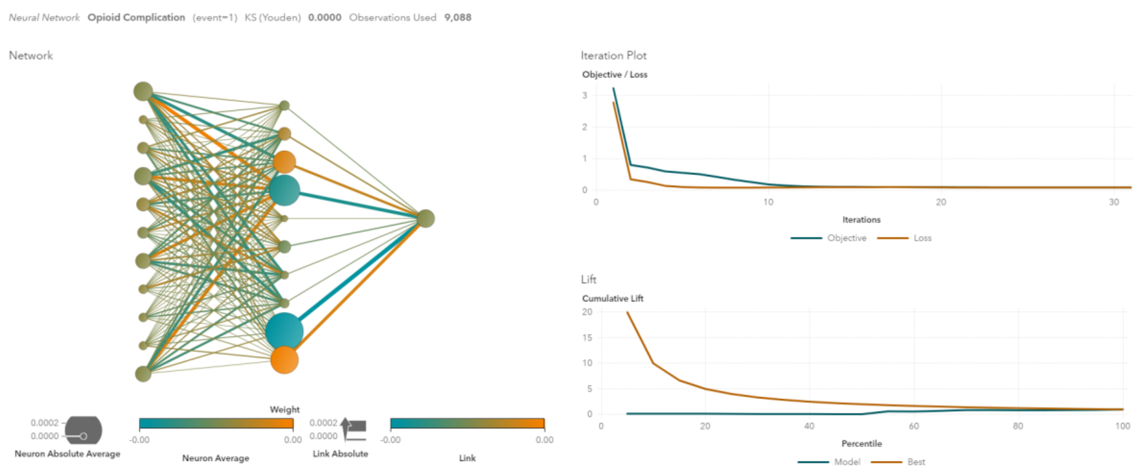

Figure 7 Neural Network Analysis to Determine Opioid Complications

MODEL COMPARISON

Using the SAS® Health Analytics Framework, all four models were compared to select the best model using KS Youden fit statistic. This showed that the decision tree was the best fit predictive model to determine the greatest contributing risk factor in opioid complications -namely a behavioral health diagnosis. Figure 8 illustrates the performance of each model using the KS Youden fit statistic.

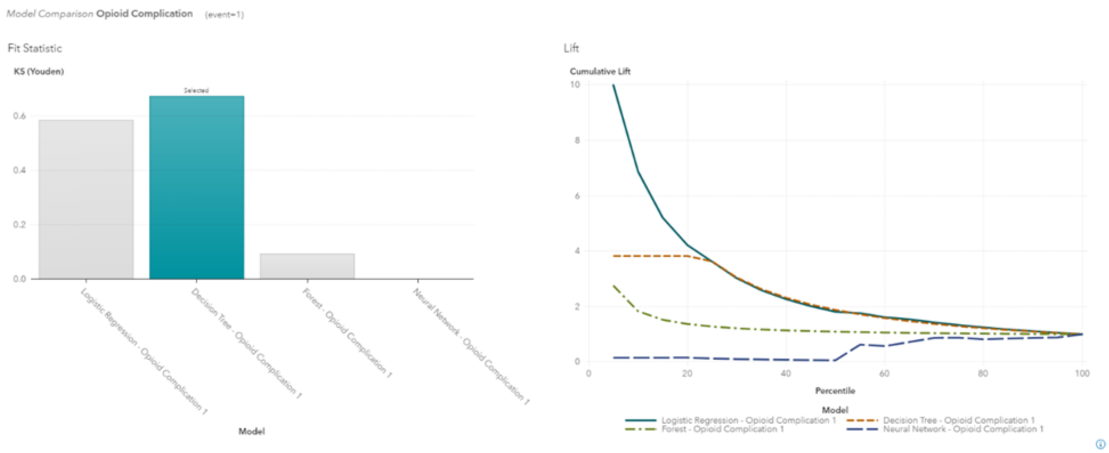

Figure 8 Model Comparison using KS Youden Fit Statistic

CONCLUSION

Although opioid complications were a relatively rare event in this patient population, it was predictable even after adjusting for comorbidities and demographic variables. SAS® Health Analytics Framework was versatile in allowing this project to be completed with machine learning models within hours instead of weeks or even months by conventional systems and methods.

We have demonstrated much quicker time to insight in a growing epidemic affecting millions of lives using this platform. The opportunity to intervene and save lives is great and timely. It is critical to identify risk factors where interventions are easily executed, and more appropriate therapies are administered to prevent negative patient outcomes, greater morbidity and mortality.

Even with these impressive findings, further studies are warranted in this space with more comprehensive patient datasets to confirm these findings in a variety of populations.

Electronic medical records should identify patients who had a previous behavioral health diagnosis to receive alternative therapies to opioids for pain management. Intervention at this patient level is crucial to stemming the opioid crisis in potentially vulnerable patient cohorts.

REFERENCES <HEADING 1>

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