Misuse of prescription opioids is a leading cause of premature death in the United States. We use state government administrative data and machine learning methods to examine whether the risk of future opioid dependence, abuse, or poisoning can be predicted in advance of an initial opioid prescription. Our models accurately predict these outcomes and identify particular prior nonopioid prescriptions, medical history, incarceration, and demographics as strong predictors. Using our estimates, we simulate a hypothetical policy which restricts new opioid prescriptions to only those with low predicted risk. The policy’s potential benefits likely outweigh costs across demographic subgroups, even for lenient definitions of “high risk.” Our findings suggest new avenues for prevention using state administrative data, which could aid providers in making better, data-informed decisions when weighing the medical benefits of opioid therapy against the risks.

Predicting high-risk opioid prescriptions before they are given

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Prescription opioids rank among the highest in terms of potential for dependence, abuse, and poisoning. In 2016, more Americans under the age of 50 y died from drug overdoses than from car crashes or gun violence, a trend driven by increases in opioid overdoses (1).

However, opioids may also be an important therapy for those who suffer from chronic pain. The majority of those prescribed opioids do not experience adverse outcomes; a survey of studies of opioid use found that rates of misuse, abuse, and addiction averaged between 8% and 12% (2). This rate is, however, higher than an early (and widely cited) claim that less than 1% of hospitalized patients receiving narcotics developed an addiction (3).

Moreover, many of those suffering from adverse outcomes were introduced to opioids through a legitimate opioid prescription. One study of 6 y of medical and pharmacy claims found that 79.9% of opioid abusers had a prescription prior to their first abuse diagnosis (4). Of the opioid abusers who did not themselves have a prior prescription, 50.8% had a family member with a prior prescription.

Given the risks and long-term consequences of adverse outcomes following legitimate opioid prescriptions, many providers now report a lack of confidence in managing their patients’ chronic pain through opioid therapy (5). Providers could benefit from better information on the risks of initiating a patient on opioid therapy, especially when that patient has never received an opioid prescription before.

Prior studies have identified risk factors for opioid abuse and dependence through descriptive analysis and statistical modeling of both medical claims and electronic health records (6–10), and two studies have also evaluated the predictive performance of such models (11, 12). However, these studies focus on individuals already persistently receiving opioid therapy and describe patterns of opioid use which are indicative of dependency and misuse within this subpopulation. Previous research has not yet developed a predictive model that is applicable to the larger population of recipients of opioid therapy using data on individuals known only prior to a prescription being given.

In this study, we use integrated administrative data to estimate models of adverse opioid-related outcomes for Medicaid enrollees in Rhode Island and conduct policy simulations of restricting opioid prescriptions to only those with low predicted risk. By some estimates, the opioid epidemic created $5.5 billion in additional health care costs to the Medicaid program nationally in 2013 (13). Estimating our model on state administrative data provides an avenue for state policymakers to predict the risk associated with prescribing opioids to Medicaid enrollees, which could be used to inform providers’ treatment decisions.

Materials and Methods

We use deidentified administrative records from a research data lake we helped build for the State of Rhode Island to support science- and data-driven policy (14). The data lake is housed in a secure enclave, and personally identifiable information has been removed and replaced with anonymous identifiers so that researchers with approved access can join and analyze records associated with the same individual across data sources while preserving anonymity (15). Because this study does not involve data that are...
both identifiable and private, Brown University’s Institutional Review Board does not classify it as research with human subjects. The database includes Medicaid records from 2005 to 2017 and data on major social benefit and insurance programs, employment, incarceration, and criminal history.

We construct a panel dataset of 80,768 individuals who received an opioid prescription or injection according to the Medicaid claims records between 2006 and 2012. (16). There are 400,024 distinct Medicaid enrollees in this period. Further details and descriptive statistics are in SI Appendix, section 2 and Table S1.

We define an adverse opioid-related outcome as receiving a diagnosis of opioid dependence, abuse, or poisoning or receiving treatment for an opioid use disorder in the 5 years following initial prescription. SI Appendix, Fig. S1 shows the cumulative frequency of adverse outcomes from the time of initial prescription, which peaks at 5.7% by year 5.

We construct variables from observations in the 12 mo prior to when an individual receives an opioid prescription. These include 84 variables for demographics, incarceration, citations, arrests, car crashes, wages, unemployment rates, household composition, and payments received from social benefit and insurance programs.

We construct 327 variables from Medicaid claims and enrolment records, including summary counts of the number of distinct diseases, chronic conditions, and procedures. The pharmacy claims data include 39,805 distinct drug product codes, and we use a pharmacological classification to consolidate drug product codes to 305 categories corresponding to 262 distinct substances. There are 8,494 distinct diagnosis codes and 6,507 distinct procedure codes observed in the claims data. We intend to simultaneously reduce the dimensionality of these variables and estimate the underlying latent structure of the occurrence of the codes. One approach is to use the preexisting hierarchical structure of the codes: to use, for instance, the fact that all ICD-9 codes grouped under a neural network (NN) corresponds to the 262 distinct substances. However, this constrains the model to nest codes in ways that may or may not be helpful for our predictive modeling purposes. For example, it is the case that codes 305.0 (nondependent alcohol abuse) and 305.2 (nondependent cannabis abuse) are together more likely to predict our outcome, as a combined measure of nondependent substance abuse? Or is it 305.0 together with 303.0 (acute alcoholic intoxication) and 303.9 (other and unspecified alcohol dependence) a broader measure of alcohol use? Because we do not know a priori how to optimally nest the codes, we instead use natural language-processing topic-modeling techniques to consolidate the codes into 50 topics, based on the text descriptions and frequencies of the codes. For example, the most 10 frequent words in topic no. 39 are “hand sprain into 50 topics, based on the text descriptions and frequencies of the codes.

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We estimate predictive models using machine-learning algorithms that search over variables and functions of those variables to maximize out-of-sample predictive fit. We fit three kinds of models: a regularized regression, an ensemble, and a neural network. These models vary in complexity (17).

For example, the prediction function from a regularized regression is a linear combination of explanatory variables whose regression weights are algorithmically selected from a set of variables and functions of those variables predetermined by the researcher. Neural networks can approximate any function, potentially delivering tighter predictive fit. However, their prediction functions are algorithmically determined layers of functions of covariates and are therefore more difficult to summarize or understand.

For the regularized regression, we use a bootstrapped LASSO (BOLASSO) with 100 bootstrap replicates to avoid arbitrary variable selection among highly correlated subsets of variables (18) and a post-BOLASSO regression on the subset of variables that are consistently selected among the 100 bootstrap replicates. For the ensemble model, we average the predictions across the 100 bootstrap replicates from the BOLASSO. For the neural network, we use a multi-layer neural network which is automatically trained to optimize the performance of the variables (19). In all models, data were split at the beginning of the study into randomly sampled training, validation, and testing sets using the ratio 50:25:25. We report the results of model predictions on the testing set (the “hold-out” sample), which was withheld from analysis prior to the preparation of this paper. SI Appendix, section 4 contains details on model implementation.

We use the model predictions to describe the potential costs and benefits of a hypothetical policy that identifies high-risk individuals before their initial prescription, prevents those prescriptions, and also prevents their adverse outcomes. Such a hypothetical policy is supported by recent findings that predictive screening tools for opioid use disorder help primary care providers improve clinical outcomes (20) and by a growing movement advising clinicians to consider patient risk before initiating opioid therapy (21). It also has similarities to the Centers for Disease Control’s Patient Review and Restriction Program for limiting opioid prescriptions (22).

We define two potential costs. Let C_{ij} denote the cost to an individual and to society of an adverse outcome for person i and C_{ij} denote the “diversion cost” experiences when diverted from an opioid therapy to an alternative therapy. This could include assignment to alternative therapies or to an opioid prescription regimen with a shorter duration and closer monitoring by and communication with a health care professional. Assuming the prescription restriction policy successfully imposes diversion costs and prevents adverse outcomes for i at a rate α, it will save the cost α(C_i - C_{ij}) for each true positive (TP) who is predicted as high risk and would have had an adverse outcome. False positive individuals (FP) accrue C_{ij} because they are predicted as high risk and prevented from obtaining an opioid prescription. The policy misses the potential savings of C_{ij} for an individual who is a false negative, someone who is incorrectly classified as low risk but has an adverse outcome. However, there is no net change since these costs would accrue in the absence or presence of the policy. Finally, true negative individuals are predicted as low risk, do not have an adverse outcome, and accrue negative costs.

The net benefit of the hypothetical prescription restriction policy for person i, therefore, is TP_α(C_i - C_{ij}) - FP_αC_{ij}. It is positive when αTP_α/FP_α > C_{ij}/C_{ij}. This captures the tradeoff between model accuracy (the probability that i is a true positive, defined as TP_α/(TP_α + FP_α), adjusted in our setting for the prevention efficacy α and its “cost ratio” C_{ij}/C_{ij}. If the diversion cost for i, C_{ij}, is low relative to the adverse outcome cost C_{ij}, then it will be beneficial to intervene at a lower risk threshold and accept a lower degree of classification accuracy and a lower diversion efficacy rate of α, C_{ij}. We can use this framework to illustrate hypothetical policy tradeoffs and to measure fairness across marginalized subpopulations.

Data Availability. Data are available through individual data-sharing agreements with each of the following Rhode Island agencies and municipal police departments: RI Department of Corrections, RI Department of Labor and Training, RI Executive Office of Health and Human Services, RI State Police, Central Falls Police Department, Cranston Police Department, Cumberland Police Department, Middletown Police Department, Narragansett Police Department, Providence Police Department, Warwick Police Department, and Woonsocket Police Department. Email hkipnas2020@ripl.org for information on how to request data for replication from the respective state agencies. Analysis code is available on GitHub at https://github.com/ripl-org/predict-opioids.

Results

Predictive Performance. A common metric for assessing the performance of a machine-learning model is the area under the receiver-operating characteristic curve (AUC), which measures the probability that, given two randomly chosen individuals with different outcomes, the model will correctly assign a higher risk to the individual with the adverse outcome. A perfect classifier has an AUC of 1, and a classifier that chooses at random has an AUC of 0.5. Our models achieve AUCs of 0.778 (95% CI 0.762 to 0.790) for the BOLASSO, 0.786 (95% CI 0.771 to 0.797) for the LASSO ensemble, and 0.801 (95% CI 0.785 to 0.812) for the neural network. SI Appendix, Fig. S2 shows that for all models, the top three deciles of predicted risk have a higher fraction of true outcomes than the full sample base outcome rate of 0.057. In our case, the less-transparent, more-complex neural network does not deliver significant gains in predictive performance.

Consistent Predictors. Fig. 1 shows the distribution of odds ratios from the post-BOLASSO regression for the 51 variables which

*This includes both opioid and heroin poisoning. See SI Appendix, section 2C for details.
the BOLASSO model selected as the strongest, consistent predictors from the full set of 1,301 variables across the 100 bootstrap replicates. BOLASSO helps to identify consistent covariates, avoiding arbitrary choices among highly correlated pairs. While the coefficients on the selected variables do not necessarily have a causal interpretation, they pick up factors which are strong predictors among observables. For example, observed claims for routine preventative health (e.g., Fig. 1, topics 4 and 10) may themselves lower risk through increased or more frequent interactions with medical professionals, or they may proxy for attention to personal health or responsibility which is the true unobserved underlying factor that reduces risk. The primary purpose of our post-BOLASSO regression is to identify strong predictors which may point us in the direction of potential underlying mechanisms for further study.

The two variables with the largest odds ratios (indicating increased risk) are related to crime: release from prison and an indicator for an arrest. Individuals released from prison in the prior year are estimated as 119% more likely to develop an indicator for an arrest. Individuals released from prison in the top risk decile if $\alpha = 1$ are labeled. A complete regression table is available in SI Appendix, Table S2.

Cost-Benefit Analysis. Whether the prescription diversion policy delivers benefits overall depends on whether it delivers benefits for those denied prescriptions. This in turn depends on how the parameters $\alpha$, $C_D$, and $C_A$ covary with $TP_i$. Assume for simplicity that $\alpha$, $C_D$, and $C_A$ do not vary across individuals and that $\alpha = 1$. Fig. 2 shows the break-even cost ratio $C_D / C_A$ which is cost neutral using predictive risk from the neural network model, with the green line assuming a diversion rate $\alpha = 1$ and homogeneous diversion and adverse outcome costs ($C_{D,i} = C_D$, $C_{A,i} = C_A$). In the top risk decile, the break-even ratio is 0.233: It is net beneficial to recommend against opioid prescriptions for individuals in the top decile if $C_D$ is less than 23.3% of $C_A$. It is net beneficial to intervene with the entire population if $C_D$ is less than 5.7% of $C_A$.

The existing literature provides guidance on reasonable estimates for $C_D$ and $C_A$, and we detail the calculation for an estimate of $C_A \approx \$450,000$ (2010 dollars) in SI Appendix, section 5 and Table S4. Diversion costs are more difficult to quantify. They may include lost productivity due to chronic pain after receiving an alternative therapy, or they may include lost time due to requirements for more frequent monitoring of high-risk individuals by prescribing physicians. The economic cost of pain in the United States is conservatively estimated at $560 to $635 billion, with a value of lost productivity from $299 to $335 billion (23). Treating pain compassionately is a moral imperative for physicians, who must balance protecting those experiencing
chronic pain with the significant risk of harm that opioids can cause individuals, their families, and their communities (24). However, recent research suggests that opioid therapy may not be more effective at pain relief than nonopioid therapy in both the short and the long term. A randomized trial comparing opioid therapy to nonopioid therapy for acute short-term pain found similar levels of pain relief between the two treatments (25), and observational studies also show no advantage for opioid treatment in terms of pain relief, with some patients on higher-potency opioids reporting more psychological impairment than those on lower-potency opioids (26, 27).

Estimates of costs of time are often calculated and utilized in the transportation literature. The value of time (VOT) has been estimated using stated-preference surveys as well as using revealed preference methodologies (28, 29). Typical VOT estimates are on the order of $30/h (30). Using a 2,000-h work year, the VOT estimate would correspond to a $60,000 annual loss in productivity if diversion costs resulted in loss of 1 y of full-time VOT.

This suggests that \( C_D \) is likely lower than the $104,400 break-even cost (23.2% of $450,000) for the top risk decile predicted by our model at \( \alpha = 1 \); $104,400 is above the 86th percentile of the annual earnings distribution in the United States in 2017 (31). Thus, a low risk threshold that maximizes true positives at the cost of increased false positives could be optimal. These findings support a growing belief among some within the medical community that the risks of opioid prescription outweigh the benefits in many cases of prescription outside of cancer or palliative care (32).

A benefit of structuring our cost–benefit analysis in terms of the cost ratio is that a risk threshold can be reevaluated as better data on these costs become available or as knowledge about opioid dependency improves. For example, the cost–benefit analysis represented by the green line in Fig. 2 assumes perfect prevention of dependency for predicted high-risk individuals as a result of the policy (\( \alpha = 1 \)). Individuals may still get access to an opioid through prescriptions given to friends and family. Approximately 10.7% of dependents (50.8% of 21.1% who did not themselves have a prescription) claim friends and family as the source of their first opioid (4), and diversion may still fail if those who do not receive a prescription subsequently borrow pills from others. An \( \alpha \) of 0.893 (the red line in Fig. 2) would assume that 10.7% of people go on to seek opioids from a friend or family, and true positives would then develop a dependency. In this case, the break-even costs for the top decile would be $95,400 (21.2% of $450,000).

Furthermore, high-risk individuals who are diverted to alternative therapies could have a higher rate of seeking and obtaining alternative opioid sources (e.g., \( \alpha_i \) and \( TP_i \) are negatively correlated). This may occur, for example, if opioid addiction is rational. Rational addiction models (33) predict that those seeking doctor prescriptions for opioids may be rationally seeking them prior to their first prescription to form an addiction as a fully informed, forward-looking, rational decision. Therefore, while restricting opioids may raise the cost of acquiring them and decrease the total number of prescribed opioids, diversion effectiveness may still be imperfect if those seeking prescriptions are making a rational choice and are therefore more likely to obtain opioids and develop a dependency even without a prescription.

To explore whether rational addiction may drive first-time prescriptions for opioids, we examine data on adverse outcomes as a function of patients’ degree of knowledge that they are receiving an opioid. We use the fact that patients may receive opioids through epidural or intravenous injections during inpatient procedures. Under the assumption that these opioid recipients were less likely to be informed they were receiving an opioid than those receiving and filling a prescription from a physician, we would expect fewer adverse outcomes from opioids received through inpatient procedures than through prescriptions in a rational addiction framework. We find that, when used as an explanatory variable for dependency while controlling flexibly for observable characteristics, an indicator for opioid injection is not significantly different from zero (SI Appendix, section 6...
and Tables S5 and S6), suggesting that rational addiction may not be driving opioid prescription demand among those receiving their first prescription. Indeed, many researchers point out that informed, rational addiction decisions may be applicable to drugs like nicotine (34), but may not apply to mind-altering drugs or drugs whose effects are not widely known. In the case of opioids, there is evidence that the risks of prescription opioids and their long-term effects were not widely known to the public (35).

Our framework provides a way to adapt and evaluate policy by adjusting $\alpha$ as the information set and health and policy landscapes evolve. More generally, $\alpha_i$ and TP may be negatively correlated for other reasons. SI Appendix, section 7 and Fig. S3 present cost–benefit simulations that allow $\alpha_i$ and TP to be negatively correlated and show there exist parameters for which a policy could be less effective among the highest-risk individuals. In general, trialing a policy and evaluating outcomes would allow policymakers and scientists to uncover individual-level parameter distributions by estimating heterogeneous treatment effects. This could allow policy to improve dynamically over time and eventually predict prescription restriction efficacy for diverting adverse outcomes.

**Fairness.** In addition to evaluating the overall cost–benefit trade-off of a prescription restriction policy, our framework can help policymakers examine measures of “fairness” by quantifying the extent to which policy costs versus benefits accrue disproportionately to marginalized groups. The predictive model's false discovery rate (FDR) is defined as the fraction of false positives among all individuals who are predicted to have an adverse outcome. Differences in FDR across subgroups can occur when the model predictions $\hat{Y}$ are not independent of subgroup membership conditional on the true outcomes $Y$, which is a construct for evaluating fairness that is well cited in the literature (36, 37). Here, we focus on FDR because it represents a notion of unfairness arising from a disproportionate diversion cost accruing to individuals from marginalized groups.

Fig. 3 shows the FDR by risk decile and by minority status, incarceration history, and disability status. The previously incarcerated have a significantly lower FDR, as release from incarceration is a strong positive predictor of adverse outcomes. Differences in FDR across minority groups to negate overall predicted benefits from prevention policies (SI Appendix, section 8 and Table S8). Our predictive modeling and cost–benefit approach allows policymakers to quantify and weigh benefits and costs within and across subpopulations when designing a data-driven preventative policy.

**Discussion**

Prevention and treatment policies can be complementary approaches to opioid use disorders. Treatment can help the many individuals already suffering from adverse outcomes, while prevention can stem the growth of new cases of opioid dependence, abuse, or poisoning.

The proven standard treatment for opioid use disorder is medication-assisted treatment (MAT) (38–40). However, it faces two significant hurdles. First, MAT is not widely available to those with opioid use disorders; only 36% of substance abuse treatment facilities offer one of three different kinds of medication treatment (41). Second, even when those suffering from opioid use disorders can be connected to treatment, the costs associated with treatment are high and recovery from an opioid use disorder is challenging. The probability of recovery after a year of MAT is estimated at 50% (42).

Prevention strategies can help prevent further cases of opioid use disorder. Current strategies are primarily designed around reducing the quantity or potency of opioid prescriptions to curb misuse and prevent poisoning among those with existing opioid use disorders.† These strategies are especially complementary to a treatment approach. A recent study suggests that limiting

†For example, a major health insurer's effort to reduce extended-release oxycodone prescription by requiring prior authorization led to an increase in the rate of short-acting opioid prescriptions and no overall change in the total morphine milligram equivalents prescribed (43).
opioid availability for those with an existing disorder may increase the use of illicit drugs such as heroin.‡

The most widespread approach to preventing misuse by those with a disorder has been the deployment of prescription drug monitoring programs (PDMPs). These electronic data systems present data on the prescription history of controlled drugs to providers and are now in use in almost every state (40). They have been shown to reduce prescription rates of opioids and increase provider comfort in prescribing opioids, as providers can be reassured that they are not enabling risky opioid-dependency-related behaviors such as doctor shopping or receiving multiple overlapping prescriptions (45, 46).

These strategies are reactive rather than proactive; they target individuals who have already begun opioid treatment and have likely developed dependency. Our models complement these policies by providing an opportunity to predict high-risk prescriptions among the larger population of patients based on their characteristics and health histories before an opioid prescription is given for the first time. The models can be applied to the broader population of Medicaid enrollees, alerting physicians to possible risk when an opioid prescription is being considered, along with, for example, risk indicators of existing dependency from prior opioid prescription patterns.

Our models and hypothetical policy aim to prevent dependency before it occurs. This is complementary to existing efforts and could make use of the infrastructure already in place, such as the PDMPs. For example, a PDMP could implement our modeling approach to show providers a risk categorization for all patients (e.g., a red, yellow, or green indicator for predicted risk). This could increase information available to providers, expand the population covered by the PDMP, and help providers consider the benefits and risks of initiating opioid therapy with a new patient.

The information policy could be implemented without disclosing particular and potentially sensitive information about the individual not known to the physician. By determining a threshold based on rough high-risk/low-risk categories, it may be possible to both protect privacy and communicate valuable information to support health care professionals in determining the best course of treatment for their patients. For example, the mean rate of prior incarceration in the top two risk deciles is 9.7%, implying that being in the highest-risk deciles does not imply an individual is highly likely to have a prior criminal record.

Moreover, diversion costs may be small and effectiveness relatively high as the number of opioid prescriptions will be reduced, reducing the probability of unintended dependency. Once dependency occurs, MAT typically costs $6,552 to $14,112 annually (47) and is estimated to be effective 50% of the time (42). This means that for 1,000 individuals, it would cost $5.7 to $12.3 million over and is estimated to be effective 50% of the time (42). This means that for 1,000 individuals, it would cost $5.7 to $12.3 million over and is estimated to be effective 50% of the time (42).

Our definition of adverse outcomes is limited by the accuracy of diagnosis codes. Prior studies have found that opioid-related diagnoses can be underreported because of their potentially stigmatizing nature. Although it is unknown precisely what fraction of opioid use disorders go undiagnosed, Carrell et al. (50) found that diagnosis codes were missing for as many as one-quarter of patients for whom their providers were aware of opioid abuse. Similarly, a study by Barocas et al. (51) estimated that only 44% of individuals with opioid use disorder were identified as such in claims and administrative records. To address this limitation, we added an adverse outcome based on procedure codes for the treatment of opioid use disorder, which could indicate an adverse outcome even in the absence of a diagnosis.

Including treatment as an indicator of adverse outcomes is also a limitation. As noted in prior work, receiving treatment for an opioid use disorder is a positive outcome conditional on already having a disorder (51, 52). However, the goal of this study is to suggest opportunities for prevention by examining whether individuals at a high risk of developing an adverse outcome can be identified with confidence before they are given a prescription using administrative data. This complements important research being done on successfully treating opioid use disorders after they have occurred (53).

Rhode Island has a research data lake that enables predictive modeling using cross-agency data. While any state or county could develop a similar research data lake (14, 15), restricting our predictive model to use only Medicaid claims and enrollment data yields nearly the same accuracy as models using integrated, cross-agency data. This is because, in the case of opioid dependence, Medicaid claims data contain many variables correlated with key predictors found in non-Medicaid data. For example, Medicaid enrollment data contain information on prior incarceration through payer codes related to receipt of health services while incarcerated, indicating an incarceration in the base period. They also contain data on demographics, family structure, and income from the application process. SI Appendix, Figs. S5–S7 replicate Figs. 1–3 using only data from Medicaid in the predictive model, with minimal changes in the results.

That being said, all models achieve an AUC near 0.800, indicating they have strong predictive power but could still be improved. While the Rhode Island data lake is uniquely rich in the connected and anonymized administrative records it holds, it contains only medical claims records from Medicaid. Those receiving a first prescription outside of Medicaid and developing a dependency diagnosed in Medicaid records, or vice versa, will cause decreased predictive accuracy in our model. Expanding the data to include, for example, state-wide electronic health records to examine impact on predictive fit, false positive rates,
fairness, and cost–benefit analysis of diverting opioid prescriptions from those predicted to have high dependency risk is an important topic for future research.

Conclusion

The opioid epidemic is a complex public health challenge that requires policy solutions spanning prevention to treatment and recovery. Our results demonstrate the feasibility of an approach to primary care based on intervening with high-risk initial prescriptions through predictive modeling. Our data-driven, machine-learning approach to modeling adverse outcome risk provides insights into the benefits, costs, and fairness of policies limiting opioid prescriptions. Intervening at the earliest stage, before an individual receives an initial opioid prescription, has the potential to prevent future treatment costs and recovery challenges and, ultimately, the life-long consequences of opioid use disorders.

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