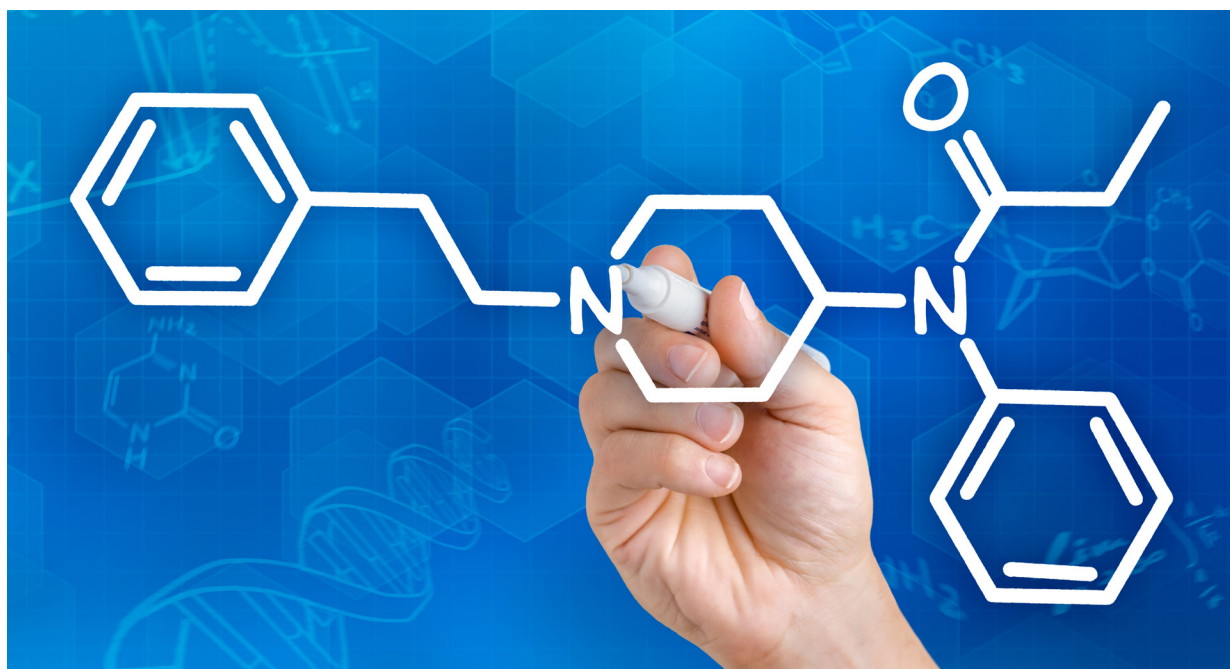


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Ten insights on the US opioid crisis from claims data analysis

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Ten insights on the US opioid crisis from claims data analysis

Careful analysis of health insurers' claims data can provide important insights into the opioid crisis by identifying patterns that could help shape strategies to combat opioid dependence and abuse.

The opioid crisis remains one of the United States' most alarming and daunting public health problems. Combatting the crisis is far from easy. However, a rich source of data that could help inform discussions about ways to address opioid abuse—and improve pain management practices—is available: health insurers' claims.

Here, we share ten insights we developed through claims analysis.¹ These insights are intended to spark both dialogue and further investigations. They may raise more questions than they answer, but we believe that even identifying the most important questions to ask will be valuable for tackling the crisis.

First, however, we would like to acknowledge two limitations in our analysis. Because we used data sets from several state Medicaid programs, our insights cannot always be generalized to all payer contexts or all geographies. Also, while we believe that claims analysis alone can produce robust findings, we acknowledge that other data types—clinical and nonclinical—could increase precision. Nevertheless, the insights we developed and questions they triggered demonstrate the help that claims analytics can provide in identifying underlying issues and developing more rigorous initiatives to battle the crisis.

INSIGHT 1

Opioid prescribing is widespread—it does not result primarily from outlier prescribers.

As the media often notes, a small set of prescribers has very high opioid prescribing rates. In our analysis, the top 1% of prescribers were responsible for only 5% of all opioid prescriptions and 21% of morphine-equivalent doses (MEDs).² However, the next one-quarter of prescribers were responsible for 50% of the prescriptions and nearly 70% of all MEDs.

Question for discussion:

- How can initiatives to improve opioid prescribing patterns engage many, if not most, prescribers?

INSIGHT 2

Prescribing patterns vary significantly by geography, even among patients undergoing similar types of care.

The rate of opioid prescribing varies among regions and communities, even when measured within a single type of care. Exhibit 1 illustrates this in patients undergoing treatment for low back pain. We found, for example, that opioid dosing patterns (as measured by MEDs per day) varied by 75% or more across zip codes. Furthermore, there was little consistency in dosing patterns. Some zip codes had high opioid prescribing rates but total MED

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¹Our analyses used only limited data sets, anonymized beforehand in full compliance with HIPAA privacy and security rules, and with permission from the state Medicaid agencies that had provided the data.

²There are many types of opioids. To compare dosing levels among them in an apples-to-apples way, a standard approach is to convert an opioid dose into what is called a morphine-equivalent dose (MED). (A MED is also sometimes referred to as a morphine-milligram equivalent, or MME.) For more details, see the technical appendix.

Ten insights into the opioid crisis

- 1 Opioid prescribing is widespread—it does not result primarily from outlier prescribers.
- 2 Prescribing patterns vary significantly by geography, even among patients undergoing similar types of care.
- 3 Within a single region, prescribing patterns often vary significantly, even when providers are treating similar clinical problems or types of patients.
- 4 Even within an individual provider's clinical practice, opioid prescribing patterns may vary significantly, depending on the type of problem being treated.
- 5 Patients with opioid use disorders are heterogeneous, but can be grouped into archetypes.
- 6 Providers frequently prescribe opioids to patients with known or potential risk factors for abuse.
- 7 In one analysis, more than one-third of the patients had a known or potential risk factor for abuse.
- 8 Patients with concurrent prescriptions for an opioid and a behavioral health condition appear to have a 30% or greater likelihood of developing future opioid dependence.
- 9 Most opioids are prescribed by providers other than the natural “quarterback” of a patient's underlying complaint or condition.
- 10 A small portion of opioid use originates in emergency departments.

dosing close to median levels. Other zip codes exhibited the opposite pattern.

This heterogeneity held true for many other factors related to the opioid crisis. We spotted geographic variations in the frequency of doctor and pharmacy shopping, the rates of opioid prescribing by specialty and condition, and access to prevention and treatment resources.

Drilling deeper into these geographic differences, we used social network analysis to identify patterns of prescribers and pharmacies that appeared to be associated with an increased risk of opioid prescribing—and thus might be areas to prioritize for intervention. We found

that in some communities, opioid prescription fills were concentrated in a few pharmacies, even though the providers “linked” to those pharmacies had average prescribing rates. We also observed the opposite: in other communities, a few prescribers stood out from the pack, but no subset of pharmacies had a disproportionate concentration of opioid prescription fills.

Questions for discussion:

- How can strategies to combat the opioid crisis best avoid a “one-size-fits-all” approach to program design, and instead tailor approaches and resourcing to match local needs and dynamics?

- How can advanced analytics be used to define common patterns of the effect the opioid crisis is having on communities, which could then be used to help guide the design and execution of local responses?

INSIGHT 3

Within a single region, prescribing patterns often vary significantly, even when providers are treating similar clinical problems or types of patients.

Many analyses have compared opioid prescribing rates among a large group of providers or within a single specialty. However, that approach does not take into account differences

in the types of patients being treated. We believe that the best lens to use for comparison is an episode of care (all the treatment needed for a given condition over a defined length of time).³ The episode lens allows apples-to-apples comparisons on prescribing practices because it enables comparisons within similar clinical scenarios.

Using this approach, we found—not surprisingly—that the rate of opioid prescribing was much higher for many types of procedural care, such as orthopedic surgery, than for acute medical care (e.g., headache management or the nonsurgical treatment of low back pain). In fact, we found that for many proce-

EXHIBIT 1 Opioid prescription rates and dosing patterns vary considerably from region to region

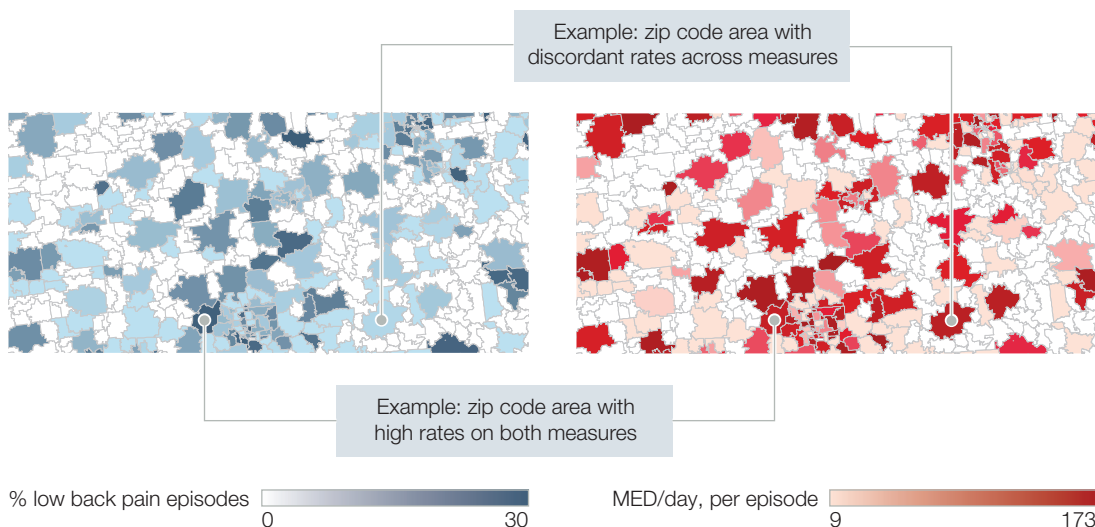
[BLINDED DATA VISUALIZATIONS]

Rate of opioid prescriptions for low back pain, by zip code area¹

% of episodes with opioid prescriptions

Dosing patterns (MED/day) for low back pain, by zip code area¹

Average MED/day² among episodes with opioids



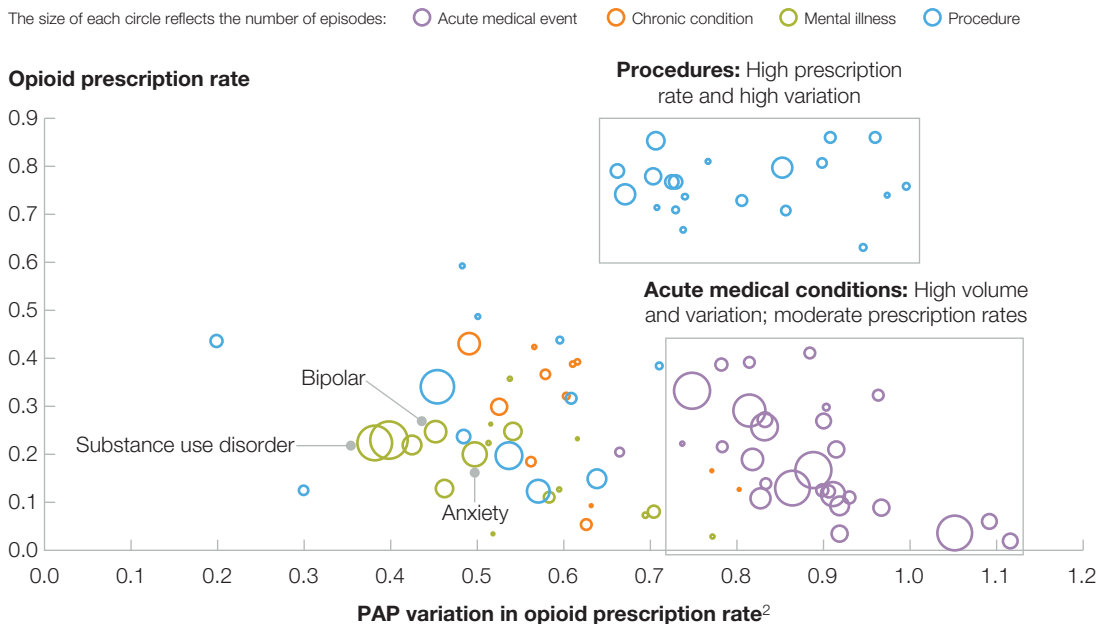
¹The group studied were low-back-pain patients treated by providers who had managed at least five episodes of low back pain (with or without the use of opioids). Prescribing and dosing patterns were calculated throughout the 30-day episode duration.

²MED/day, morphine-equivalent dose per day (see the technical appendix).

Source: Sample state Medicaid claims, CY 2015

³See the technical appendix for a fuller discussion of episodes of care.

EXHIBIT 2 Opioid prescription rates vary both across and within similar clinical scenarios



¹Opioid prescription rate is the percentage of episodes during which one or more opioid prescriptions were filled.

²The PAP, or principal accountable provider, can be considered the “quarterback” of an episode because he or she is responsible for most of the care delivered. This analysis is based on patients treated by PAPs who managed five or more similar episodes that included at least one opioid prescription.

Source: Medicaid claims data

dures, opioids were prescribed, on average, in more than 70% of the episodes. But within the same type of episode (almost regardless of the episode type), prescribing rates varied greatly, with highest-quartile episodes associated with a 50% to 100% greater incidence of opioid prescribing than median episodes.

Even when we looked at specific episodes, we still found that opioid prescribing rates varied widely (Exhibit 2). For example, we learned that some providers never prescribe opioids for sprains; others always do. These patterns were consistent. Other types of acute medical care also had large variations in opioid prescribing rates (although at rates

generally lower than those in procedural episodes).

Questions for discussion:

- What would it take to drive greater agreement, both in theory and in practice, on how providers should treat pain for the same clinical conditions?
- What are the most effective ways for provider associations and state and federal health agencies to develop and clarify guidelines and best practices in pain management? And what is needed to increase compliance with them?

INSIGHT 4

Even within an individual provider's clinical practice, opioid prescribing patterns may vary significantly, depending on the type of problem being treated.

In our analysis, a provider's high opioid prescribing rate for one type of episode often failed to predict his or her prescribing rates for other episodes—even when the episodes were similar. For example, we compared prescribing rates

among the providers who were “quarterbacks” for three orthopedic episodes: ankle sprains, knee sprains, and shoulder sprains. Almost none of the providers exceeded the median in opioid prescribing rates for all three of the episodes—but nearly 90% of them had at least one episode type with a rate above the median (Exhibit 3).

These results suggest that even for the same provider, pain management practices with opioids are not consistent across episodes.

EXHIBIT 3 Prescribing patterns vary even within a provider's clinical practice, depending on the condition

Random sample of 15 providers

● MED per day¹ below median, in comparison with peers ● MED per day¹ above median, in comparison with peers

Provider	Ankle sprain	Knee sprain	Shoulder sprain	Has at least one episode above median
1	●	●	●	✓
2	●	●	●	✓
3	●	●	●	✓
4	●	●	●	✓
5	●	●	●	✓
6	●	●	●	
7	●	●	●	✓
8	●	●	●	✓
9	●	●	●	✓
10	●	●	●	✓
11	●	●	●	✓
12	●	●	●	✓
13	●	●	●	
14	●	●	●	✓
15	●	●	●	✓

¹MED/day, morphine-equivalent dose per day (see the technical appendix).

Source: Medicaid claims data

Questions for discussion:

- How might providers consider not only their opioid prescribing rate relative to their peers, but also how their pain management practices apply to specific episodes of care?
- What are the most promising opportunities to engage most, if not all, providers—even those who typically appear to follow guidelines—

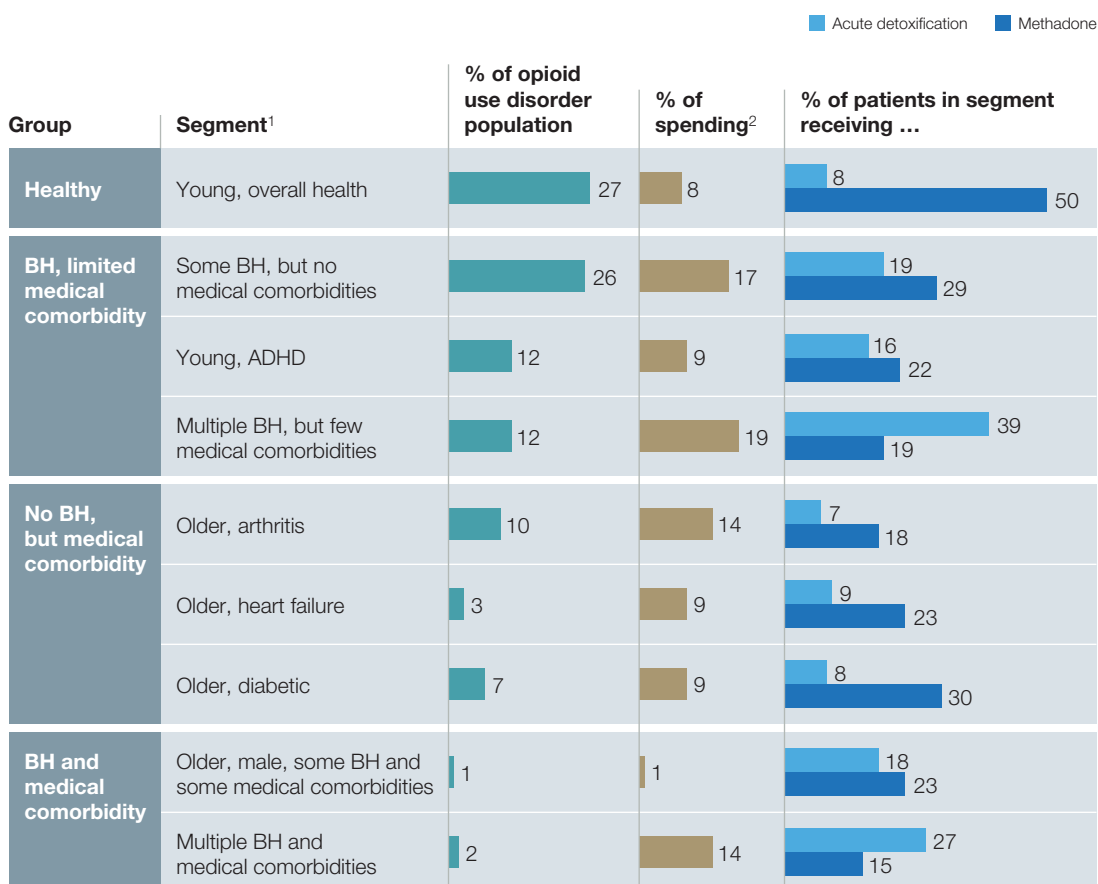
and encourage them to consider whether they need to alter their prescribing patterns?

INSIGHT 5

Patients with opioid use disorders are heterogeneous, but can be grouped into archetypes.

Cluster analyses indicate that patients with opioid use disorders can be grouped into several different archetypes (Exhibit 4). While

EXHIBIT 4 Cluster analysis makes it possible to group patients with opioid use disorders into addressable segments



ADHD, attention deficit hyperactivity disorder; BH, behavioral health.

¹In this analysis, "young" was defined as 35 years of age or less; "older" was defined as greater than 50 years old.

²Share of total medical, pharmacy, and behavioral health spending for patients with opioid use disorder.

Source: Medicaid claims data

the patients may have opioid use in common, other factors—including the concurrence of behavioral health and medical conditions, and socioeconomic factors—correlate strongly with different utilization patterns (e.g., emergency department (ED) and inpatient use, overall cost to the health system).

Furthermore, treatment patterns appear to be influenced by these other factors—the archetypes differ greatly in their ranges and rates of methadone use (15% to 50%) and acute detoxification treatment (7% to 40%).

Questions for discussion:

- To what extent are the treatment programs that work for some patients likely to work for others?
- What might be done to effectively categorize patients, stratify their risk, and match them to the most effective treatment protocol?

INSIGHT 6

Providers frequently prescribe opioids to patients with known or potential risk factors for abuse.

A separate analysis found that 60% of the providers had prescribed opioids to patients with at least one of these features: having a non-opioid substance use disorder (SUD), being diagnosed with two or more behavioral health issues other than an SUD, filling opioid prescriptions from more than four providers in the past six months, or using more than four pharmacies to fill opioid prescriptions in the past six months.

In recent years, data-driven efforts have intensified to equip providers with more information about the patients to whom they are prescrib-

ing pain medications. But even though the use of electronic health records has increased, aggressive action is still needed to close the gap in transparency, knowledge, and practice.

Questions for discussion:

- What factors are contributing to opioid prescribing to patients with known or potential risk factors?
- Do providers know about these risk factors and prescribe opioids anyway, or are they unaware of them? If they are unaware, is the problem difficulty in accessing patient data (e.g., via electronic medical records or a prescription drug monitoring program), or is it a failure to seek the information?

INSIGHT 7

In one analysis, more than one-third of the patients had a known or potential risk factor for abuse.

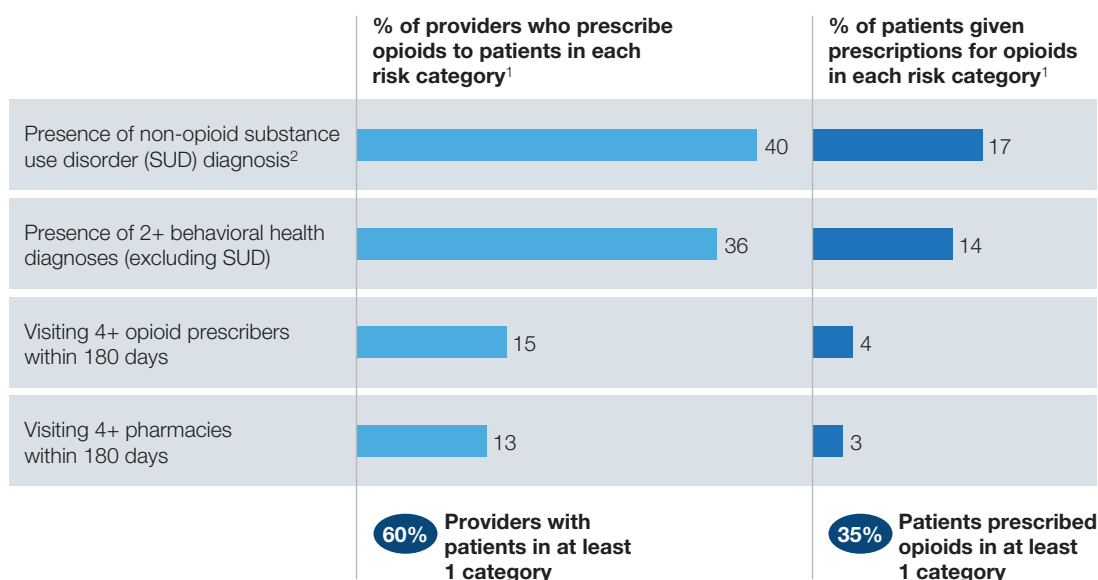
Approximately 35% of the patients given opioid prescriptions in our analysis had features that put them at increased risk for opioid abuse (Exhibit 5). The features we found most often were the presence of a non-opioid SUD (17%) and the presence of two or more behavioral health diagnoses other than SUD (14%).

Questions for discussion:

- For patients who receive opioids but have risk factors for abuse, what are the most effective care pathways and interventions to mitigate the risk?
- How do these pathways and interventions differ, based on a patient's specific risk profile?

EXHIBIT 5 More than one-third of patients given opioid prescriptions may be at increased risk for abuse

% (not mutually exclusive among individual risk factors)



¹Within a one-year time period around the opioid prescription; risk categories are not mutually exclusive.

²Non-opioid SUD diagnoses exclude caffeine, nicotine, and tobacco use.

Source: Medicaid claims data

INSIGHT 8

Patients with concurrent prescriptions for an opioid and a behavioral health condition appear to have a 30% or greater likelihood of developing future opioid dependence.

We performed claims-based predictive modeling to identify which patients using opioids were most likely to be diagnosed with opioid dependence or an opioid use disorder within the next year. The model identified several factors associated with future opioid dependence (Exhibit 6). For example, each prescription filled for a behavioral health condition (assuming all else was equal) was associated with a 2.5% to 4.6% increase in the likelihood that a patient

using opioids would develop dependence or abuse within the next year. (The comparison was with patients using opioids but not taking a behavioral health medication.) This finding suggests that a patient who took a behavioral health medication for one year could have a 30% or greater increase in the risk of developing future opioid dependence or abuse.

In our study, additional factors found to be predictive of future opioid dependence or abuse included the presence of a behavioral health diagnosis such as anxiety, bipolar disorder, or recent suicide attempt (regardless of whether a behavioral health medication had been prescribed) and certain demographic factors (e.g., age 35 to 44).

We agree with healthcare researchers and policymakers that the integration of additional data sources (e.g., from social media, the criminal justice system, or prescription drug monitoring) would enrich our predictive modeling. Nevertheless, our claims-based model alone produced promising results—a 66% capture rate and 76% overall accuracy.⁴ Predictive modeling is critical to better inform providers and enable them to improve their pain management practices.

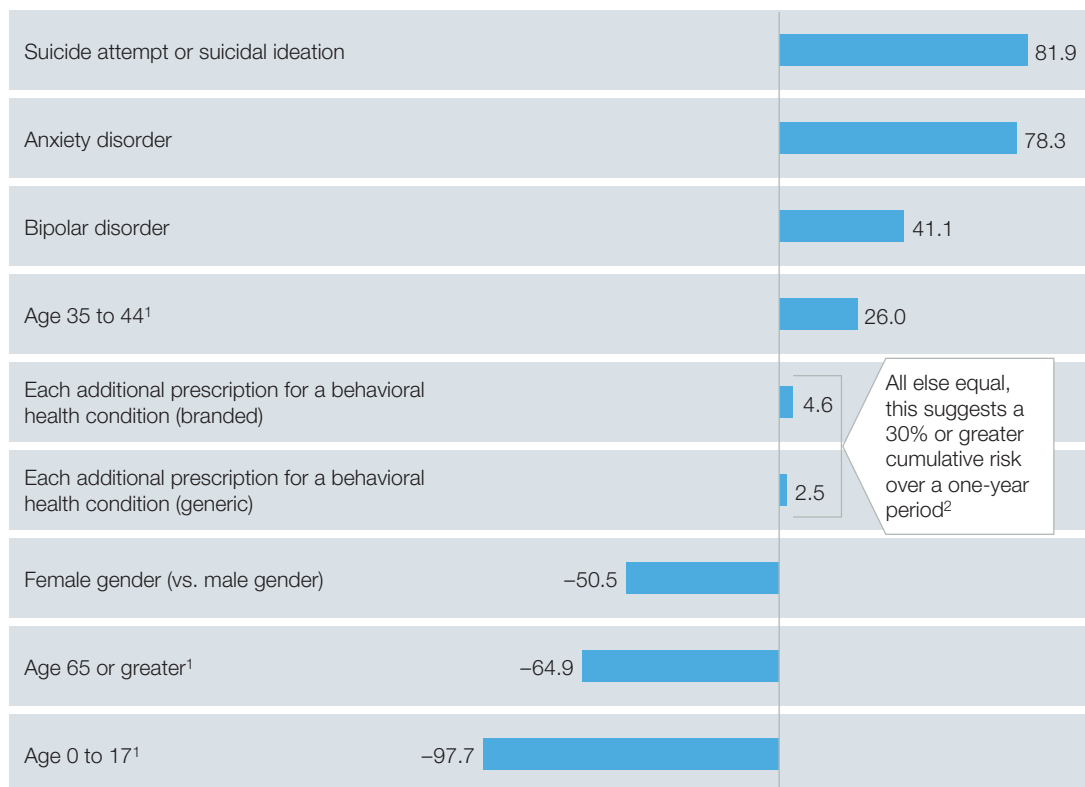
Questions for discussion:

- To what extent do the correlations we found imply causality? In particular, what are the interactions between opioid use and behavioral health conditions?
- How could (or should) a patient's risk profile and predictive modeling influence practice patterns, medical and pharmacy policy, clinical guidelines, and care management protocols?

EXHIBIT 6 Predictive modeling can identify risk factors for opioid dependence

Risk factors that were statistically significant for opioid dependence

% increase or decrease in risk



¹ Compared with a reference category of those age 18 to 34.

² Assumes 12 months of pharmacotherapy within one year (i.e., cumulative risk of $(1.025\%)^{12} = 1.344$, or a 34% increase in risk).

Source: Medicaid claims data

⁴ See the technical appendix for explanation of capture rate and overall accuracy.

INSIGHT 9

Most opioids are prescribed by providers other than the natural “quarterback” of a patient’s underlying complaint or condition.

Analysis of one episode (spinal fusion) showed that nearly 80% of the total MEDs used by patients were not prescribed by the surgeon who had performed the procedure and who was responsible for the immediate “patient journey” after the procedure (we refer to such a provider as the principal accountable provider, or PAP).⁵ Furthermore, there was no apparent relationship between the amount prescribed by the PAP and the total amount prescribed by all providers during the episode.

This finding makes clear that high-dose prescribers and multi-prescriber patterns are separate issues—and both are important to address. All providers should recognize that they are part of a care team for a patient’s pain management and should make efforts to be aware of what other providers are prescribing to their patients.

Questions for discussion:

- Should the provider accountable for most other aspects of a patient’s care pathway also be responsible for managing that person’s pain, including the appropriate use of opioids when indicated?
- If so, what strategies and tools can best enable providers to influence others’ prescribing patterns, whether the other providers are in their own practice or are consultants or specialists their patients see throughout the course of care?

INSIGHT 10

A small portion of opioid use originates in emergency departments.

In our study, opioid prescribing in the ED was both less frequent and contributed less to total MEDs than was prescribing by other providers in other care settings (e.g., primary care physicians or outpatient specialists). In our analysis of spinal fusion and low back pain episodes, EDs accounted for only 5% of the opioid prescriptions and 1.4% of total MEDs. Among the low back pain episodes, 10% of the prescriptions and 1.2% of total MEDs came from the ED.


Questions for discussion:

- How can EDs improve their pain management practices, even though the proportion of opioid prescribing coming from EDs is low?
- How can comprehensive opioid strategies address both ED and non-ED prescribing patterns?



We believe these ten insights can improve collective understanding of the opioid crisis in the United States and have identified important questions to answer. The insights concentrate on providers and patients in the healthcare delivery system. Additional work is needed, especially a widening of the aperture to focus on contributing factors beyond providers and patients. Options that should be included are investigation of non-claims data sources, integration of data sources, and a mix of descriptive, predictive, and prescriptive analytics to improve the design of opioid initiatives.

⁵Note that the prescription analysis was done at the level of the prescribing or rendering physician, not at the physician practice level.

Nevertheless, this analysis represents a robust starting point. Despite the complexity of the crisis, our growing ability to use data and analytics to uncover granular—and sometimes counterintuitive—insights is a reason for optimism. If we ask the right questions, we can advance our collective understanding and address the crisis more effectively, rapidly, and comprehensively. 

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Technical appendix

Our analyses used only limited data sets, anonymized beforehand in full compliance with HIPAA privacy and security rules, and with permission from the state Medicaid agencies that had provided the data.

Data

Data and population overview

- In the analyses, we identified opioid prescriptions, substance abuse, and/or overdoses using claims data from state Medicaid members (about 750 million claims in total). Sources included inpatient and outpatient facility claims, professional claims, and pharmacy claims from the period January 1, 2014 to December 31, 2016.
- Given the specific characteristics of the Medicaid population, the insights described in this paper may not be generalizable to the entire US population.

Data cleaning and processing

- McKinsey hosts data on a cloud-based HITRUST-certified platform. Before the data is stored, it is iteratively cleaned and standardized. A data diagnostic identifies gaps in scope and quality that may affect the accuracy of analytic output.
- The standardized data is used in McKinsey's proprietary data model and supplemented with third-party and proprietary information to enable insight generation in McKinsey's set of analytical tools.

Methods

Episode of care definition

- Episodes of care are clinical situations that have relatively predictable or determinable start and end points, such as procedures, hospitalizations, acute outpatient care, and some treatments for chronic conditions. Episode analytics can be used to identify the provider in the best position to affect the clinical outcomes and total costs associated with an episode of care. The episode analytic construct can then be used to assess (through retrospective analysis of claims data and episode-specific risk adjustment for case mix) the outcomes achieved and costs incurred for each episode.
- Here, episode analytics allow for a fairer “apples-to-apples” evaluation of provider performance and a “patient journey”-based view to identify and measure opioid-related practices.
- A principal accountable provider (PAP) is the provider in the best position to affect clinical outcomes and total costs associated with an episode. A PAP is identified by the provider's ID field on the professional claim that includes the given procedure or the diagnosis that identifies the member's episode. In the context of opioid prescribing, the PAP may or may not be the only professional who prescribes opioids to patients. PAP variation is defined mathematically as: $(75\text{th percentile PAP performance} - 25\text{th percentile PAP performance}) / \text{median PAP performance}$.
- Examples of the output of episode-based analytics are shown in Exhibits 1, 2, and 3.

Technical appendix *(continued)*

Episode archetypes

- Episode archetypes are aggregations of individual episodes of care into broader groupings based on similarities in patient journeys. Exhibit 2 reflects two of the archetypes (acute medical events and procedures) and labels some examples of the mental illness archetype:

- Procedures (e.g., perinatal care, colonoscopy, knee arthroscopy, total hip replacement)
- Acute medical events (e.g., shoulder sprain, acute congestive heart failure exacerbation, headache, urinary tract infection, pneumonia)
- Mental illness (e.g., depression, substance use, anxiety, schizophrenia)
- Chronic conditions (e.g., osteoarthritis, rheumatoid arthritis)

Calculation of morphine-equivalent dose (MED)

- To create an “apples-to-apples” comparison of opioid dosages, the morphine-equivalent dose (MED) is used for analysis. This unit is defined as:

$$[\text{Total MED}] = [\text{strength}] \times [\text{conversion factor}] \times [\text{quantity}]$$

- The list of opioid national drug codes (NDCs) and associated conversion factors can be found on the CDC website: <https://www.cdc.gov/drugoverdose/resources/data.html>

- The MED methodology is used in Exhibits 1 and 3.

Predictive model methodology

- The predictive model was developed based on one state’s Medicaid population by taking members who were enrolled continuously for a two-year period (CY 2015–16), had received one or more opioid prescriptions in the first year, and had not been diagnosed with an opioid use disorder. As stated above, all data used in our analyses were anonymized before use, and all data procedures were fully compliant with HIPAA privacy and security rules and other applicable privacy laws. The outcome variable of the model was a binary variable classified by any diagnosis of opioid use disorder in the second year. The explanatory variables tested in the model reflected only 2015 data and included 31 behavioral health conditions, 15 chronic medical (non-behavioral health) conditions, race, gender, age, and behavioral health pharmacotherapy utilization. Oversampling of those with a future opioid use diagnosis was performed to create a case/control ratio of 1:5. The specific algorithm used to develop the model was a stepwise logistic regression model.
- The data was split into training and validation data sets using an 80/20 ratio. Although the metrics displayed represent results from the training data set, comparable results were found on the validation data: AUC = 0.732 and 0.738 for training and validation, respec-

Technical appendix *(continued)*

tively. (AUC stands for area under the receiver-operating characteristic, or ROC, curve.)

- Finally, model performance was tested across several risk thresholds to make predictions of a future diagnosis of opioid use disorder. A model that optimized for the best overall predictive accuracy—measured by the sum of sensitivity (i.e., capture rate) and specificity—uses a risk cutoff of 4.3% and has a sensitivity of 66% with a specificity of 77%, whereas a model that uses a risk threshold of 10% has a sensitivity of 22% and a specificity of 97%. Future consideration as to which risk threshold is preferable may be based on the business case it is used for (e.g., avoiding prescribing to high-risk members vs. targeted outreach or treatment interventions).
- Overall accuracy is defined as the percentage of patients correctly classified as their future category (i.e., the number of those correctly identified as having future opioid use plus the number of those correctly identified as having no future opioid use, divided by the sum of all patients).
- Outputs of this predictive modeling are found in Exhibit 6.

Social network analysis

- Social network analysis (SNA) is a process to describe social structures using networks and graph theory. It is generally useful in identifying influential individuals and structural or temporal patterns associated with unusual interactions

(e.g., fraud, waste, abuse). The model can be applied to a multitude of interactions among a set of individuals having these interactions.

- In the opioid SNA, nodes represent individual prescribers that are part of an interconnected network as linked by their patients who receive opioid prescriptions. The analysis allows, for instance, the identification of member-level “doctor-shopping” behavior and prescriber or pharmacy-level concentrations of shared high-risk patients.
- Social network analysis is referenced in Insight 2.

Cluster analysis

- Clustering is a bottom-up approach to classify patients, based on their characteristics and past utilization patterns, into different groups. Groups are determined based on algorithms to minimize deviation for members within a group while maximizing deviation for members across groups. In this example, the k-means algorithm was used on similar patient-level characteristics as those used in the predictive model (e.g., 31 behavioral health conditions, 15 chronic medical conditions, etc.).
- This approach helps to identify discrete patient segments with varying needs who may respond differently to interventions. Stakeholders (e.g., payers, providers) can use this more granular understanding of patients to tailor interventions (e.g., care management) appropriately.
- Cluster analysis is shown in Exhibit 4.