## Background

Studies have reported the dramatic rate of increase in sales of opioids, which have paralleled the rise of opioid abuse and mortality associated with these drugs. To attempt to control these trends, numerous initiatives have been developed to address the abuse of opioid analgesics. One means of providing early identification of potential abusers and prevent misuse of opioids is through the use of prescription drug monitoring programs (PDMPs). Despite the documented testing of a validated model in more than one national health plan, to ensure applicability and generalizability across the US.

## Methods

### Two predictive models of opioid abuse were developed, validated and tested: 1) For the overall 2010 sample, 30 variables were identified as being associated with pain in an ROC analysis of opioid abuse and 2) for the subset of subjects with an opioid prescription (Table 10).

### For model development, members newly diagnosed with opioid abuse in 2010 were identified using the following CD-ROM clinical codes:

- **DIAG**: Opioid type (age or gender appropriate)
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### The results of diagnostic accuracy were calculated at three different levels: 1) for all subjects, 2) for those with pain diagnosis and 3) for those with no pain diagnosis.

### Members were required to have 210 days of continuous enrollment pre-index, no prior diagnosis of opioid abuse or opioid poisoning, not be in a skilled nursing facility for 30 days, not be claimants for pregnancy.

### A random sample of commercial members without an opioid abuse diagnosis was identified in the 2010 data as a control group. A ratio of 3:1 (controls:cases) was used in developing the model.

### A stepwise logistic regression model was applied to a list of 24 variables considered to be potential risk factors. These included:

- 1 opioid prescription, 2 opioid prescriptions, total opioid prescriptions, number of opioid prescriptions, 2 opioid prescription, 2 opioid prescription, 2 opioid prescription, 2 opioid prescription.

### 1 visit to a mental health care, 1 mental health care visit, opioid use, and/or benzodiazepine use.

### Age, gender, ethnicity, geographic region of residence.

### Undergraduate chronologies were developed, including high school, college, and postgraduate education, and/or training.

### The resulting model for the 2010 commercial plan membership, and finally applied to a subset of the Truven Health Markets\textsuperscript{\textregistered} Commercial Health Plans' National Behavioral Insights and Surveillance dataset.

## Results

### The overall model was applied to the 2011 commercial membership that qualified for inclusion in the study (n=831,149) and had an accuracy level of 89.6% at a .05 (Table II). The model for the subset of members with a prescription for opioid was applied to the 2011 commercial plan membership that qualified for inclusion in the study (n=103,780; cases,104,174) and had an accuracy of 87.3% (Table III, II).

### False positive rates observed at test were very low; however, the sensitivity rate of such models was also low. In statistics at test were slightly lower than those obtained during model development (Table 2A, B).

### The generation of the models developed from data in the health plan were tested using the Truven dataset comprised of data from over 100 health plans. The models were applied to a random sample and performance of the models was approximated for the specific health plan population.

### The resulting diagnostic models for the sub-population of opioid users (cases = 1,161) had an efficiency of 62% at the cutoff of ≥ .05 (Table 3).

### As prescribers are sensitive to patients with opioid abuse, key metric was a low false positive rate, i.e., scoring a member as a risk for a diagnosis of opioid abuse when such a finding was unknown. A probability of ≤ 0.05 was deemed acceptable though the statistical accuracy of the resulting model for the sub-cohort of opioid users (cases = 1,161) had an efficiency of 82% at the cutoff of ≥ .05 (Table 3).

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### The models were evaluated for diagnostic accuracy on the 2011 commercial plan membership, and finally applied to a subset of the Truven Health Markets\textsuperscript{\textregistered} Commercial Health Plans' National Behavioral Insights and Surveillance dataset.

## Discussion and Recommendations

### This study demonstrated that predictive models of opioid abuse developed and tested using human data can be successfully applied in other health plans without loss of model performance.

### The risk factors identified are consistent with the published literature that reported the following as important risk factors for opioid abuse: co-morbidity conditions, history of visits with mental health services, mental health diagnoses, substance abuse, opioid abuse, and/or hepatitis diagnoses. However, one important limitation of these published studies was the timing of the opioid use diagnosis appeared contrary to when risk factors start to become established. These predictive models were collected. Any intervention designed and implemented with the goal of prevention in mind would need to rely on risk factor identification well before the potential diagnosis.

### In order to confirm the clinical and economic value of implementing any intervention programs intending to address the opioid epidemic, programs need to be developed and tested for efficacy and cost-effectiveness. This paper is not designed to address the question of whether the selected model was the best model or should have been used.

### When testing the model, utilize plan-specific coefficients to predict the risk of diagnosed opioid abuse.

### Determine whether members accurately predicted to be diagnosed with opioid abuse (or their providers) will participate in interventions and custom design interventions taking this knowledge into consideration.

## Limitations

### The tradeoff between specificity and sensitivity was continually examined during model validation and testing. One limitation of comparing the tradeoff for the model is that the model did not identify a cut-off point that was likely to result in a high number of false positives or was the equivalent of as many cases as hoped. Given this tradeoff, further examination of a higher number of false positive cases would lead to a better tradeoff for determining if their pattern of opioid use was consistent with the clinical and/or demographic profile of opioid abuse in their observable future.

### Limitations common to studies using administrative claims data may be applicable to the current study, and may include lack of certain information in the database (e.g., lab results, weight, and health behavior information) and error in some existing data. It is not possible to ascertain from this study, as it is an observational study, using retrospective claims data. Although multivariate regression modeling was used to reduce selection bias and improve the statistical power of the model, this is only reduce bias caused by measured covariates. It cannot reduce bias caused by unmeasured covariates.

## Conclusion

### The objective of this study was to develop, validate and test predictive models of opioid abuse and develop useful data to understand the factors that contribute to the development of opioid abuse. The model did not identify any single factor that was likely to result in a high number of false negatives or was the equivalent of as many cases as needed. Given this tradeoff, further examination of interested in the model did not identify a cut-off point that was likely to result in a high number of false positives or was the equivalent of as many cases as hoped. Given this tradeoff, further examination of a higher number of false positive cases would lead to a better tradeoff for determining if their pattern of opioid use was consistent with the clinical and/or demographic profile of opioid abuse in their observable future.

### The selected model was the best model or should have been used.