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Background

RxOA has become a major social problem in the United States¹⁻⁶

- **Emphasis on development of risk management approaches to maximize the benefits of prescription opioids (RxOs) while minimizing the risks associated with abuse⁷**
- **Annual per patient direct health care costs for RxO abusers more than eight times higher than for non-abusers⁸**
- **Estimated societal costs of RxO abuse in U.S.**
 - **Total societal costs \$11.8 billion**
 - **Health care costs \$3.5 billion⁹**
- **Issues**
 - **Abuse and diversion of RxOs**
 - **Under-treatment of pain for those with legitimate need for RxOs by limiting RxO access**



Data-Driven Approaches to Identifying At-Risk Patients is Important to Multiple Stakeholders

Payers

- Identifying at-risk individuals important to control health care costs, address fraud, and provide quality care

State Public Health and Controlled Substance Authorities

- Prescription monitoring program administrators need validated cutoffs for threshold reports
- Public health authorities need validated methods for characterizing and identifying at-risk individuals and communities

Federal Government

- National prescription monitoring legislation requires a rational implementation

Clinicians

- “External” outcome measures critical for assessing clinical outcomes



Project Objectives

1. **Develop a model based on prescription drug claims data for prescription drug monitoring programs (PMPs) to help identify patients at risk for prescription opioid abuse, dependence and mis-use (RxOA)**
2. **Develop a model based on medical claims data (with information on medical services utilization and comorbidity risk factors) to help identify patients at risk for RxOA**
3. **Combine the two models to create a hybrid model to help identify patients at risk for RxOA**

Risk Factors

Drug Claims

- **Demographic features**
 - Age
 - Gender
- **Utilization parameters**
 - Number of RxO prescriptions
- **At-risk behavior**
 - Pharmacy shopping
 - Physician shopping
 - Refilling RxO prescriptions early
 - Escalating RxO dosage over time

Medical Claims

- **Demographic features**
 - Age
 - Gender
- **Medical diagnoses**
 - Non-opioid substance abuse, depression, PTSD, hepatitis, cancer, and fibromyalgia
- **Medical treatment facility visits**
 - Hospital
 - Mental inpatient



Data

Data from the Maine Health Data Organization¹⁰

- **Contains all privately insured drug and medical claims in Maine from January 1, 2005 through December 31, 2006**
 - **De-identified information**
 - **Approximately 800,000 patients (~146,000 with at least one RxO claim)**
 - **Drug claims data fields include**
 - **National Drug Codes (NDCs) to identify the actual drug and its associated dose, date of fill, days supply, and (de-identified) pharmacy and prescribing physician identifiers (the latter information available beginning in September 2006)**
 - **Medical claims data fields include**
 - **ICD-9-CM codes to identify the diagnosis associated with a medical claim and the type of facility that the patient visited (e.g., hospital, physician's office, mental inpatient/outpatient facility)**



RxOA Definitions

- **RxO “user” sample criteria**
 - All patients between ages of 12 and 64 years
 - At least one claim for an RxO
 - At least one medical claim during 2005-2006
- **RxO “abuser” sample criteria**
 - Same as above and additionally having at least one medical claim associated with the following ICD-9-CM codes)
 - Opioid type dependence (304.0)
 - Combinations of opioid type with any other (304.7)
 - Opioid abuse (305.5)
 - Poisoning by opiates and related narcotics (965.0) but excluding poisoning by heroin (965.01)



Logistic Model

The model has the following general form

$$\text{Log}\left(\frac{p_i}{1-p_i}\right) = \alpha + \sum_{j=1}^J \beta_j X_{ij},$$

where

- p_i is the probability that a patient i is an RxO abuser via ICD-9-CM codes
- α and β_j are the parameters to be estimated
- X_{ij} are the risk factors

ROC Curves

The performance of various algorithms was evaluated using the area under the Receiver Operating Characteristic (ROC) curves

- **The ROC curves were used to assess overall fit**
 - **Higher area under the ROC curve indicates better fit**
 - **An area under the ROC curve equal to one indicates perfect predictive power, whereas an algorithm with weak predictive power is described by the 45-degree line (i.e., an area under the curve equal to 0.5)**
- **The framework sought to develop the curve with the optimal trade-off between sensitivity and specificity**
 - **A curve with the most correct predictions of abuse (true positives) for any given level of false positives was preferred**



Model Selection Criteria

The logistic model was estimated using forward step-wise regression

- **To identify the “best” model, the following criteria were used**
 - **Area under the ROC curve**
 - Evaluated using the c-value
 - A curve with the most correct predictions of abuse (true positives) for any given level of false positives was preferred
 - **Parsimony**
 - A model with a smaller set of relevant independent variables was preferred
 - **Statistical significance**
 - Variables with a p-value of less than 0.10 and an adjusted odds ratio greater than 2.0 were preferred
 - **Clinical relevance**
 - Variables that were clinically relevant based on existing literature and research were preferred



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Hybrid Analysis

■ Sample selection

- Followed each patient for the entire 2005-2006 time period combining data from drug and medical claims analyses
 - 134,542 eligible patients
 - 984 patients identified as abusers (0.73% of eligible patients)

■ Summary of results

- The c-value for the best ROC curve was 0.924
- A sensitivity cut-off of 0.80 yields a specificity of about 0.92
 - Identifying 80% of the abusers would result in a 8% false positive rate

Implications and Discussion

- **Models to identify patients at risk to RxOA were successfully developed**
 - **Using prescription drug claims data**
 - **Using medical claims data**
 - **Via a hybrid model using both drug and medical claims data**
- **Using ICD-9-CM codes underestimates RxOA since these conditions are infrequently diagnosed by physicians**
 - **Therefore, the actual number of patients in the Maine sample with RxOA may be significantly higher**
 - **As a result, a substantial number of false positives may actually be true positives**

Next Steps and Potential Future Directions

- **Dissemination**
 - Manuscript forthcoming: *American Journal of Managed Care*
- **Payer application**
 - Create generic algorithm for payers to screen for patients at risk for prescription opioid abuse
 - “Added value” in payer meetings
 - AG could create model customized to payer database
- **Public health application**
 - Create model of public health implications of abuse-deterrent opioids
 - In addition to cost savings estimates, could also include: hospitalizations, ED visits, poisonings, deaths, absenteeism/presenteeism, criminal costs, etc.
- **Extend analysis for more generalizable results**
 - Conduct analysis over longer time period to assess prior medical history as a determinant of future opioid abuse, dependence and misuse behavior
 - Use Analysis Group employer database to analyze over different geographic areas/nationally



Sources

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