

# Application of a Novel Medication-Related Risk Stratification Strategy to a Self-Funded Employer Population

Adverse drug events (ADEs) are a major public health issue, and identifying which patients in a large population require targeted interventions can be quite difficult. Computational tools developed with clinical and pharmacological data can be highly valuable for identifying those patients. This project presents the application of a novel risk stratification tool that utilizes only medical claims data to identify members at high risk of ADEs in 2,528 members from a self-funded employer population. Algorithms were designed to score five different risk factors to personalize the patient's risk for quick mitigation via health care professional interventions. In total, 15,911 medications were considered in the analysis, indicating an average of five medications per member (ranging from one to 48 medications per member). In total, the tool was able to identify 324 members (12.8%) considered at high risk for ADEs. Furthermore, 61 members (2.4%) considered at the highest risk for ADEs were identified by isolating those members who were in the high-risk groups for all five medication risk factors. In conclusion, our results indicate that a risk stratification tool based on medical claims cannot only quickly identify high-risk members but also can provide insights into how to intervene and prevent costly medical expenditures.

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Adverse drug events (ADEs) are a major public health issue. Studies have shown that drug-drug interactions (DDIs) and associated ADEs may cause up to 4.4% of all hospital admissions.[1] Furthermore, preventable ADEs and DDIs prolong hospital length of stay by an average of 3.4 days, increase the average cost of treatment by $3,511 and elevate the risk of death.[2,3] According to a 2007 Institute of Medicine report, approximately 1.5 million preventable ADEs occur annually in the United States.[4] These events can even translate into death—For the last ten years, the Center for Drug Evaluation and Research reports that ADEs rank between fourth and sixth as a leading cause of mortality.

Fortunately, DDIs and ADEs are avoidable with proper recognition of interacting drug combinations as well as appropriate actions.[5] *Appropriate actions* largely refers to pharmacist and prescriber interventions to mitigate multidrug interactions occurring within patients ingesting potentially dangerous drug combinations. Mitigating these risks is relatively quick and easy for trained health care professionals; however, identifying which patients require these types of medication risk interventions within a large health care population has been a much more difficult task. Because health care clinics are comprised of a mixture of healthy patients taking no medications as well as patients with multiple medications and comorbidities, there is a need for resources and tools that help direct the limited resources of clinical pharmacists to patients at greater risk of experiencing ADEs.[6]

Population stratification systems using different descriptive variables such as demographics, past consumption of health resources and health status have been developed and put in place to offer effective and efficient intervention directions. These have been implemented within various care settings to predict medical care costs and health care outcomes and to reimburse third-party payers. For example, diagnosis-based models such as the Johns Hopkins Adjusted Clinical Groups® (ACGs) system, the 3M Clinical Risk Groups (CRGs) software, the Clinically Detailed Risk Information System for Cost (CD-RISC), and the Centers for Medicare & Medicaid Services (CMS) Diagnostic Cost Group, Hierarchical Condition Category models (DCG/HCC) have been developed and implemented in various health care settings.[7-11] Models such as LACE Index, PEARL score or FAM-FACE-SG also have been developed to predict hospital readmission.[12-15] The goal of all of these tools is to identify patients at high risk for health care-related issues for risk mitigation purposes and, thus, to decrease health care service utilizations and medical costs.

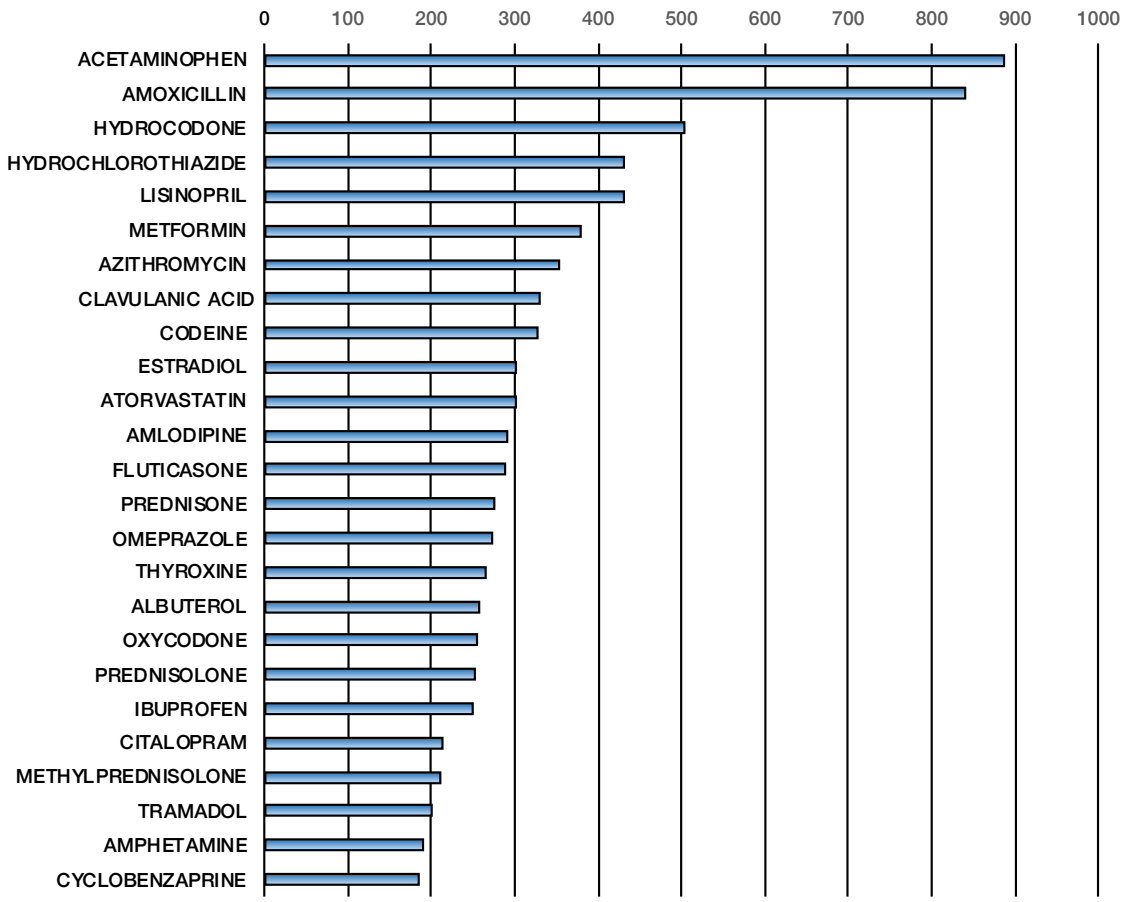
Several of these models are robust systems from a statistical point of view and have been proven useful in public and private health organizations. However, despite their capability to predict a significant portion of the variability in population use of health services, they also have significant limitations.

1. They rely on the appropriateness of diagnosis coding: Hierarchies are often imposed, so a person is coded for only the most severe manifestation among related diseases.
2. Some models use simplified and limited lists of disease codes, leading to unrecognized or underreported conditions.
3. The predictive value of these models is directly linked to the timely coding and reporting of patients' conditions. Significant lag times (months or even years) can be observed in some claims data files.
4. Most models do not include information such as lifestyle or socioeconomic variables.
5. When prescription information is included, drug categories rather than actual drugs prescribed and their characteristics are used as covariables. For instance, von Korff developed a model where drugs were used as a proxy to define codes for *International Statistical Classification of Diseases and Related Health Problems, Ninth Revision (ICD-9)* and then to relate the predictive model to disease state.[16]
6. Information generated by these risk stratification strategies are not immediately actionable.
7. In all of these models, the consideration for multidrug interactions and the significant risk of drug-related adverse events is rather absent or omitted.

This work presents the application of a novel tool that fulfills the need for a population-based medication risk stratification and personalized medication risk score to an employee population of a self-funded employer. The scoring of this medication risk stratification tool utilizes pharmacological characteristics of medications and patients' drug regimen data. By incorporating a multitude of clinical data, and through algorithmic development, the tool not only identifies high-risk members of the population but also produces

**FIGURE 1**

**Visualization of the Top 25 Medications Within This De-Identified Population**




personalized medication risk snapshots, empowering health professionals to quickly generate recommendations for mitigation of the established risks.

## Methods

### *Data*

Originating from a self-funded private employer, the data utilized in this project were de-identified claims data over the period of about one year (January 1, 2015 to March 1, 2016). Prior to any statistical characterization, the claims were processed into regimen snapshots. To do this processing, the most recent dispense date of each unique member was identified and the day difference between that date and every other dispense was calculated. If the days' supply of the individual dispense was greater than the day difference between that dispense date and member's most recent dispense date, then the claim line was considered to be part of the member's current regimen. Following the creation of all de-identified snapshots, the drugs within each member regimen were mapped to their active ingredient(s) via National Drug Code (NDC) coding. Following this active-ingredient mapping of de-identified member regimens, statistical characterization and risk stratification analyses were performed.

### *Risk Stratification*

To characterize the risk of the population and identify those at high risk for medication-related problems, a novel risk stratification tool was employed. Using literature and clinical guidance, this tool is designed to look at five factors related to

medications and their potential to cause ADEs. These factors are the number of prescribed medications, indexes of cognitive impairment, indexes of sedation, risk of heart-rhythm impairment and competitive inhibition of the drug regimen. By examining these factors using specially designed algorithms, as well as a final algorithm to combine all factors into an overall risk score, the medication risk of each individual as well as the entire population was characterized.[17] Members were considered at high risk for ADEs if their medication risk score was 20 or higher. Furthermore, each risk factor was characterized with high risk-score thresholds ranging from four to seven, depending on the factor. Members who were in all five high-risk groups were considered to be at the highest risk for ADEs.

### *Statistical Methods*

This project utilized a variety of computational tools such as SQL Server, MySQL, R, and Microsoft Excel to classify, characterize and analyze the claims data and member population. String count queries and various grouping analyses in conjunction with scoring thresholds were conducted to characterize prescription drug prevalence, determine population demographics and identify high-risk members of the population. Following the population and risk characterization, visualizations of these characterizations as well as risk score distributions were generated using Microsoft Excel and R.[18]

## Results

### *Population Demographics*

The analyses indicated that the de-identified population consisted of 2,528 members. The average age of the members was 40 years old, ranging from one to 85. In total, 15,911 medications were considered in the analysis, indicating an average of five medications per member while ranging from one to 48 medications per member. The top five medications being taken in this population were acetaminophen, amoxicillin, hydrocodone, hydrochlorothiazide and lisinopril, respectively. The top 25 drugs being taken in this population can be found in Figure 1. Furthermore, it is worth noting that six of the top 25 medications were analgesics—four different opioids and two different co-analgesics.

**TABLE**

**Summary of the High-Risk Groups as Identified by the Risk Stratification Tool**

| | Number of Members at High Risk | Percentage of the Population |
|---|---|---|
| Medication Risk Score | 324 | 12.8% |
| Substance Risk | 420 | 16.6% |
| Cognitive Impairment Risk | 265 | 10.5% |
| Sedation Risk | 445 | 17.6% |
| Heart-Rhythm Impairment Risk | 181 | 7.6% |
| Drug Interaction Risk | 362 | 14.3% |

61 members (2.4%) are included in ALL high-risk groups.

### *Risk Stratification Analysis*

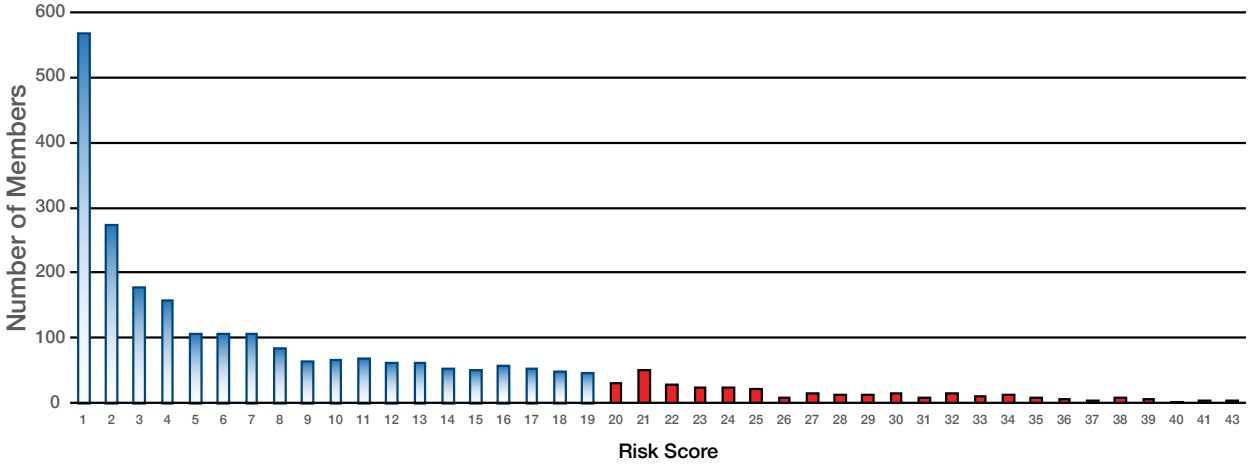
In total, the tool was able to identify 324 members (12.8%) considered at high risk for ADEs. Even further, 61 members (2.4%) considered at the highest risk for ADEs were identified by isolating those members who were in the high-risk groups for all five medication risk factors. The tool found that 362 members (14.3%) in this population are at high risk for mitigative multidrug interactions. Another interesting finding is that the tool identified 181 members at high risk for heart-rhythm impairment due to their drug regimen, which puts them at higher risk for torsades de pointes and therefore sudden death. Since this is a working-age population, it is also worth noting that 420 members (16.6%) are at high risk for sedation, which could be quite significant for a self-funded employer to be aware of. The entire high-risk grouping identification results can be found in the table, and the visualization of the medication risk score distribution can be found in Figure 2. The results not only identify those patients at high risk for ADEs but also provide succinct information as to what they are at high risk for. An individual risk visualization output from this tool can be found in Figure 3.

## Discussion

In this study, we demonstrate that a risk stratification strategy that uses

**FIGURE 2**

**Visualization of the Distribution of Medication Risk Score Across the Entire Study Population**




only medication claims data to identify patients at increased risk for ADEs is possible. This strategy presents multiple advantages over more traditional methods of risk stratification for a variety of reasons, the biggest of which is the timely identification of high-risk members. The ability to apply a risk stratification tool to quickly identify members of a population at high risk for ADEs is quite valuable. By utilizing the presented tool to score risk factors that are actionable by health care professionals, mitigation of risk is possible and can be performed quickly.

The results of the analyses of the presented tool are quite significant when referenced against the notion that this is a self-funded employee population. This means the employer is at direct risk for the financial burdens incurred by its employees' health issues and medical care costs. By identifying high-risk members for overall medication health risks as well as for various actionable risk factors related to medication health, one can prevent costly ADEs. This directly impacts employers, especially those who are fully at risk for their employees' medical costs. By employing the risk stratification tool presented in this project, health care professionals can quickly be directed toward those members who require actionable risk mitigation. In addition to directing health care professionals to high-risk members, the tool is able to create personal snapshots of why the member is at high risk. This key feature allows those responsible for the health care of their members to act quickly and efficiently to mitigate medication risks before they turn into doctor's office visits, emergency room visits, hospitalizations and other costly medical interventions.

The risk stratification and mitigation strategies presented in this work have powerful impacts outside of just preventing costly medical billings. For example, decreasing the sedation levels of a member's drug regimen may not have a direct effect on doctor's office visits, but it can certainly affect the member's quality of life. It is quite simple to understand that an employer does not want its employees to be sedated and/or cognitively impaired due to their medication regimens, but identifying the employees at risk for these factors can be much more complicated. The risk stratification tool presented can do just that, with an immense potential benefit to both employees/employers and patients/care providers. When applied to a self-funded employer in particular, this concept can provide immense benefit to workplace morale and efficiency. Thus, by identifying high-risk members, this risk stratification tool can increase the health, decrease the medical expenditure and potentially increase the quality of life of an employee population.

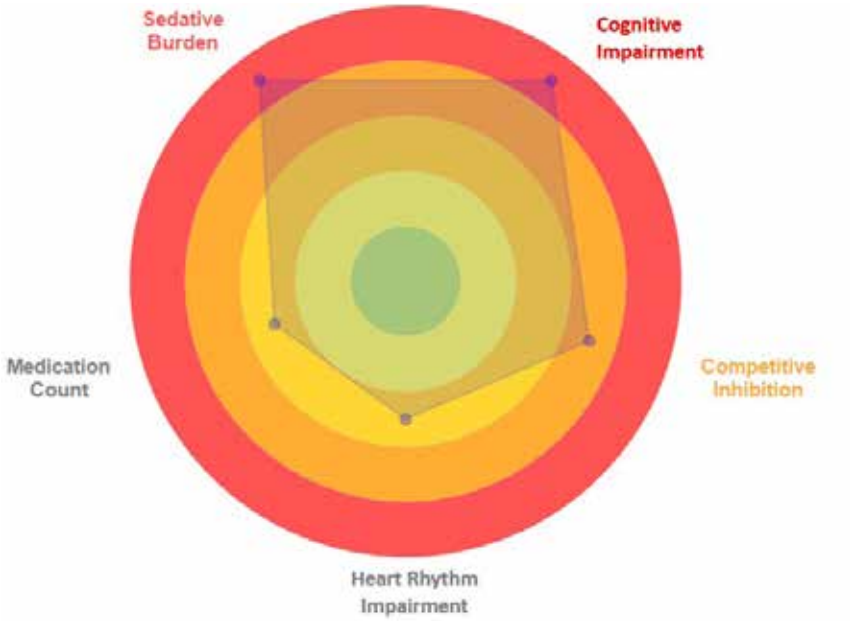
Because nearly all traditional risk stratification tools rely on diagnostic coding for risk identification purposes, timely reporting of diagnostic data is required for these analytical techniques. However, timely diagnostic coding is not always available, as observed in lag periods of international classification of diseases (ICD) coding for billing processes. However, with a risk stratification tool that utilizes only medication claims data, the reliance on diagnostic coding is eliminated.

Even further, since the presented tool only requires drug claims data for risk stratification, accuracy can be more confidently ensured. Many times, only one diagnostic code can be processed for medical billing purposes. This can be limiting for a patient who has multiple comorbidities that can go underreported in medical claims diagnostic coding. This can have a large impact on the identification of high-risk members within a population using traditional risk stratification strategies. Not only that, but identifying high-risk patients is only half of the puzzle; how to decrease those risks is just as vital as being able to identify them. The risk stratification tool presented circumvents these types of issues by providing a risk stratification strategy that relies only on medication claims for accurate results.

Since this tool relies on medication claims data for risk identification analyses, it also can be used to screen for specific drug class utilizations within a population. For instance, one can easily determine the proportion of members taking opioids and the concomitant drugs also being taken with the opioid(s). By doing so, the risk of ADEs due to these specific combinations can be calculated and targeted for risk mitigation. Not only can this be applied to opioids, but it also can be applied to virtually any drug class that is known to present severe ADEs when in combination with other specific drugs.

**FIGURE 3**

**Individual Risk Score Visualization of a High-Risk Member as Output From the Risk Stratification Tool**




## Endnotes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