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Predictive Modeling in Health Plans

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Abstract

Predictive modeling in healthcare has been gaining more interest and utilization in recent years. The tools for doing this have become more sophisticated with increasingly higher accuracy. We present a case study of how artificial intelligence (AI) can be used for a high quality predictive modeling process, and how this process is used to improve the quality and efficiency of healthcare. In this case study, MEDai, Inc. provides the analytical tools for the predictive modeling, and Sentara Healthcare uses these predictions to determine which members can be helped the most by actively looking for ways to prevent future severe outcomes. Most predictive methodologies implement rule-based systems or regression techniques. There are many pitfalls of these techniques when applied to medical data, where many variables and many interactive variable combinations exist necessitating modeling with AI. When comparing the R^2 statistic (the commonly accepted measurement of how accurate a predictive model is) of traditional techniques versus AI techniques, the resulting accuracy more than doubles. The cited publications show a range of raw R^2 values from 0.10 to 0.15. In contrast, the R^2 value obtained from AI techniques implemented at Sentara is 0.34. Once the predictions are generated, data are displayed and analytical programs utilized for data mining and analysis. With this tool, it is possible to examine sub-groups of the data, or data mine to the member level. Risk factors can be determined and individual members/member groups can be analyzed to help make the decisions of what changes can be made to improve the level of medical care that people receive.

Over the last few years, an increasingly higher degree of interest has focused on the process of predictive modeling in healthcare. While risk assessment is embedded within most industries, post industrial revolution, the process of modeling prediction using advanced mathematical models is relatively new. Within the healthcare industry, multiple constituencies operate under the principles of risk and risk assessment. In the health insurance industry this includes underwriting, actuary, finance, medical management, marketing, sales, and legal. Yet, within healthcare, the consumer often has more capacity to assess their risk of service utilization than the insurer.

Whereas trend analysis used to be a large part of actuarial and underwriting services, today more advanced mathematical models allow for clinical reporting and actuarial services to be highly integrated. This commentary is a case study demonstrating how an accurate predictive model can be created using artificial intelligence (AI), and then utilized to enhance these services. The results discussed are based on members of Sentara Healthcare (based in Norfolk, Virginia, USA), and the AI techniques discussed are those used by MEDai Inc. (based in Orlando, Florida, USA).

Sentara Healthcare is a not-for-profit regional healthcare organization that provides healthcare services and health coverage in southeastern Virginia and northeastern North Carolina in the US. Sentara operates hospitals, health plans, a medical group with over 150 leading physicians, skilled nursing and assisted living centers and home health services. MEDai, Inc. is a private company that provides clinical outcomes analysis and predictive modeling solutions for the healthcare industry as well as other industries. MEDai uses AI to provide accurate industry forecasting.

1. Value of Predictive Modeling in the Healthcare Industry

Predictive modeling is of critical value to the healthcare industry. Advanced and accurate models enable organizations to change the risk asymmetry inherent in healthcare today. This knowledge delivers improved services and improved financial modeling throughout the organization. Traditionally, underwriting and actuarial services have utilized age, gender, major diagnostic classes, and inflationary coefficients to calculate trend factors and benefit pricing.

Beyond traditional services, many modeling techniques offer the promise of improved predictive modeling. In each of these techniques the process involves rules based grouping and indirect correlations to complete the risk assessment and predictions. In each of these processes, the approach is linear and the units measured generally are in non-weighted dollars only. Both of these methodologies can yield results with minimal predictive values.

Modeling with AI offers several distinct advantages to other modeling techniques. These include:

- asymmetric weighting of continuous variables including dollars
- multiple weights for complex variables
- multiple endpoint considerations with complex weighting
- multiple technique processing
- identification of continuous variable discrimination points.

These differences create improved results as measured in accuracy utilizing multiple statistical measures (such as relative operating characteristic [ROC] curves, R^2 values, etc.)

The traditional processes can exaggerate the misconception that a dollar spent in one part of healthcare (inpatient) is identical to that in another part of healthcare (pharmacy). Consider two demographically and clinically similar patients, both consuming $US3000 in healthcare resources. However, one patient had all the costs consumed in a 3-day admission to a hospital; the other patient had all the costs consumed in prescription utilization over several months. These patients have the same financial profile but distinctly different utilization patterns that predisposes one to have additional risks for future consumption. This financial 'weighting' is easily identified within AI modeling, but not necessarily with traditional modeling. Unfortunately, several predictive models exclude specific utilization factors such as pharmacy data. In addition, other predictive models treat continuous variables such as dollars as binary variables. This further weakens a model's capacity to accurately predict utilization.

2. The Predictive Modeling Process

The entire process of clinical reporting, actuarial services and predictive modeling is both competitive and difficult. Seven critical steps are identified within the process.

The first step is data collection. Individual needs are collected within flat files or databases. Transactional systems are the backbone of the majority of these collection efforts. The second step is data aggregation. This involves combining data to create a comprehensive and relational process. This step should include a clean up process using a rules based process or other means. The third step is one of the most important. As data are collected, often is it necessary to look at or create different variables. This 'variable creation' is the capacity to look at particular data sets available and create a combination or modification to the actual variable. A simple example of this would be in the hospital setting where overall length of stay and intensive care unit (ICU) length of stay data are collected. A variable created from those two data sets might be the percent of days the patient is treated within the ICU. This variable allows review of both efficiency and potentially the complexity of cases that are occurring within a particular hospital or disease state or grouping.

The fourth step is to transform the original variables into a set of derived variables. These new variables should be created in such a way to enable more usable information to be extracted from the various predictive modeling techniques. This begins to transform the data into information. Information mining and modeling are the next two steps. Information mining is the process of reviewing available information in an intuitive and clinically relevant fashion. Critical relationships in key variables that drive significant outcomes (whether financial or clinical) require diligent examination and appreciation. Information modeling is the capacity to review those relationships and consistently look for better variables as well as predictive variables within that process.

The final step defines the mathematical relationship between the final set of predictors (known as independent variables) and the outcomes being predicted (dependent variables). In the past, largely, this mathematical relationship has been constrained to either a linear relationship using linear regression or an 'expert' set of rules with calculated weights. However, these are not necessarily the best modeling techniques for medical information.

3. Linear and Non-Linear Relationships

Stochastic forecasting began in the 17th century with gamblers who discovered the precise laws of probability. Gamblers would calculate the likelihood of any event occurring given circumstances related at a particular time. Probabilistic and stochastic forecasting continues to assign probabilities or estimates to events. More advanced predictive methodologies are referred to as forms of AI; AI utilizes a multitude of techniques to essentially 'learn' a mathematical relationship between variables by examining numerous data elements. By this definition, linear regression is a low level form of AI, as it too is a process by which a (linear) relationship is 'learned' from a sample of data elements. If all the relationships within a data set were truly linear, then the most sophisticated AI techniques would yield the same result as a linear regression.

Many kinds of non-linear relationships exist in the real world. A predictor and an outcome can have a relationship that is exponential, logarithmic, or categorical. The relationship can be a function that is increasing at one extreme and decreasing at the other. Complex clinical-financial relationships exist which regression equations cannot fully consider.

For example, let us consider the following scenario. Try to predict the outcome of a patient based on prescription drug usage and severe asthma. A predictive model using regression looks at the variables separately and reveals that both are positively correlated with more severe outcomes. Therefore, the model may predict that patients taking drugs with severe asthma will have the most severe outcomes. However, the true relationship between drug usage and being high risk occurs simply because the healthy non-asthmatics have limited reasons to be on multiple drug therapy. Reviewing sub-populations within patients with severe asthma, an observation might include the most 'at risk' patients are those not taking the appropriate drugs.

4. Role of Artificial Intelligence (AI) in Predictive Modeling

Most relationships in the medical world are non-linear. There are varieties of mathematical techniques utilized in conjunction with each other to find these relationships and collectively create a powerful predictive model. AI models can utilize neural networks, regression (linear, polynomial, or logistic), decision trees, fuzzy logic, principle component analysis, rule induction, genetic algorithms, nearest neighbors, and Kohonen Networks, as well as others.

Certainly other forms of predictive modeling exist. When one compares stochastic forecasting to heuristic forecasting there are several distinct differences. Stochastic forecasting requires uniform systems or maintains uniform systems; whereas heuristic forecasting or neural approaches are more likely aligned with organic systems. Stochastic forecasting has an *a priori* definition whereas heuristic has a feedback definition. Stochastic work is often insensitive to transient changes or micro trends and demands near complete data sets. AI works well with incomplete data sets and is extremely sensitive to these small changes. With AI the creation of new variables in nonlinear relationships between large numbers of variables makes the mathematical modeling extremely powerful. It allows for inter-relationships and the coordination of multiple variables. This is in stark contrast to what is necessary in linear regression or multivariate linear regression models. R^2 values in AI often double or even triple from traditional linear models when looking at highly sophisticated organic systems, such as healthcare.

There are a few reasons why AI techniques are criticized by statisticians and others. A poorly trained individual can purchase a neural net program over the Internet and have it examine millions of meaningless variable relationships, finding several patterns that occur by chance, and thus yielding a very high R^2 value on the data set that was used for creating the model. However, since those patterns occurred by chance in that specific data set, they will not hold true in a future data set, causing predictions to be erroneous, and yielding a very low R^2 on actual forecasting. This modeling flaw is known as 'over-fitting'. To ensure that patterns on average will hold true in the future, it is important to hold out a random segment of the data before creating a model. This is known as the 'validation set'. Then when a model is created, it is tested on this validation set to make sure that the R^2 remains high on a data set that the model has never seen before. Many consider this validation the most important test of a model.[1]

A second criticism is that people call AI a 'black box'. In linear or logistic regression, each variable gets a single coefficient associated with it. If that coefficient is high in value, it has a high positive effect on the prediction. If it is low in value, it has a high negative effect on the prediction. If it is close to zero, it has very little influence on the prediction and can possibly be removed from the model. If AI is used for a predictive model, you derive a formula just like the regression technique, except that the formula is more complicated and more difficult to understand. AI will generally have multiple coefficients for a single variable.

Recall the example with drugs and severe asthma discussed in section 3. Drugs may have a negative correlation with outcomes in the general population, but a positive correlation with outcomes in the severe asthma group. Therefore it is not possible to accurately assign a single coefficient to the drug variable that defines it as either a 'positive' or 'negative' indicator. It is likely that the regression will give drugs a positive coefficient indicating that it is a predictor of high severity. The AI will probably have multiple coefficients for that variable within the equation making its complex relationship difficult to decipher. However, that is the reality of how variables relate to each other. Indeed, this is how physicians think through the impact of pharmacotherapy. It is important to recognize this rather than force a simple relationship that is untrue and non-representative.

With AI, relationships between variables are 'trained', or 'learned'. They are not programmed nor are they parametric or restricted to be linear. This allows the methodology to better fit a model to the data sets that are available. The inter-relationship between the variables strengthens the process. Again, this is in stark contrast to typical linear statistics. Additionally, a good AI system will accommodate missing data whereas a linear regression model cannot do this. Often, because of missing data, regression models are required to exclude large blocks of data.

5. Use of AI Modeling

5.1 Predictive Modeling Comparisons

A few reports comparing the predictive accuracy of different vendors and defining an industry standard for predictive accuracy of high risk prediction models have been published. These include reports by insurers in the US relating to predictive modeling, which established both actuarial benchmark accuracies and theoretical maximums (or maximum R^2)[1] for such modeling.[2-5] In addition, earlier publications sponsored by the Society of Actuaries,[6] refer to the R^2 accuracy standard as being in the 0.15–0.20 range. A more recent study sponsored by the Society of Actuaries,[7] compared results across several predictive modeling vendors. All vendors used traditional rules-based modeling. Using a validation set consisting of 61 580 members from Sentara's health plan, R^2 values were calculated and compared (see figure 1). The highest R^2 value amongst the systems published in this article is 0.15. Using Sentara data, MEDai obtained an R^2 value of 0.31 using AI modelling. This result was further improved to 0.34 by predicting per member per month (PMPM) charges. Figure 1 demonstrates another strength of AI – the ability to effectively use and predict outliers in the model. The true R^2 values reflect this ability, and place emphasis on the outliers. While many scientists argue this is a weakness of the R^2 statistic, it should be considered a strength of the R^2 statistic in healthcare, since the high cost patients are those that require identification and sophisticated care management approaches. For example, correctly predicting high utilizers allows Sentara Healthcare to match care management resources to select specific members enabling improved clinical and financial outcomes. Artificially modifying the R^2 statistic using truncation discards hundreds of thousands of dollars in the high cost members prior to performing the calculation. This improves the appearance of systems unable to predict members in the highest cost groups, but will not 'spike' the statistics for a system using AI effectively. In the data set used for these statistics, the top 1% of the members made up 25% of the total charges. Therefore, if an organization has the resources to reduce costs in 1% of their members, perhaps by preventing catastrophic conditions, the accuracy on predicting high cost members is critical. A good performance measure to assess high risk accuracy is measuring the area under the ROC curve. With AI predictions, the areas under the ROC curves for the top 10% and 2% were 0.85 or greater (figure 2 and figure 3).

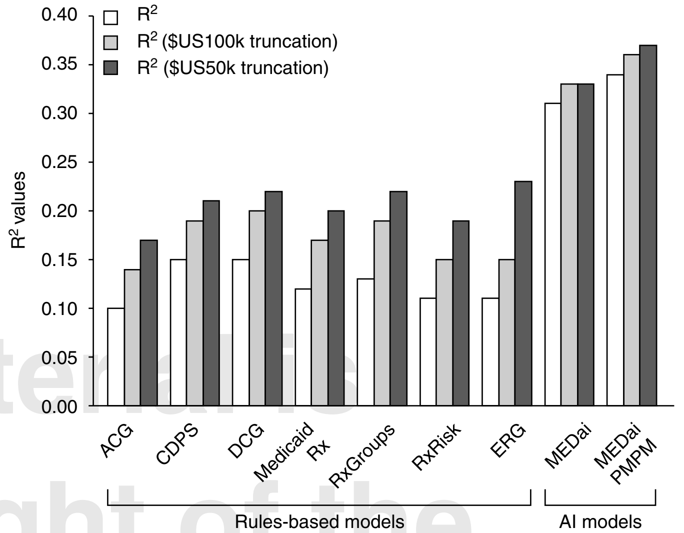

Fig. 1. Accuracy of predictive models using rules-based and artificial intelligence (AI) approaches. The figure also demonstrates how truncation of patients' costs as low as $US50 000 masks the inability to predict outliers. This artificially doubles the R^2 value.

Many methodologies convert continuous variables to binary variables to apply their relationships through a series of simple rules, losing a lot of crucial information in the process. For example, the rules may differentiate between members with and without diabetes mellitus, but may fail to look within the subset of members with diabetes to differentiate the varying levels of severity. Does a member with diabetes consuming $US10 000 carry the same risk as a member with diabetes consuming $US500 annually? Some rules-based systems will have some degree of differentiation within a disease group, but the rules have hard cutoffs which prevent the techniques from matching the level of differentiation of an AI system.

5.2 Use of AI at Sentara Healthcare

At Sentara Healthcare, there are several areas where AI predictions have become the mathematical backbone. The High Risk

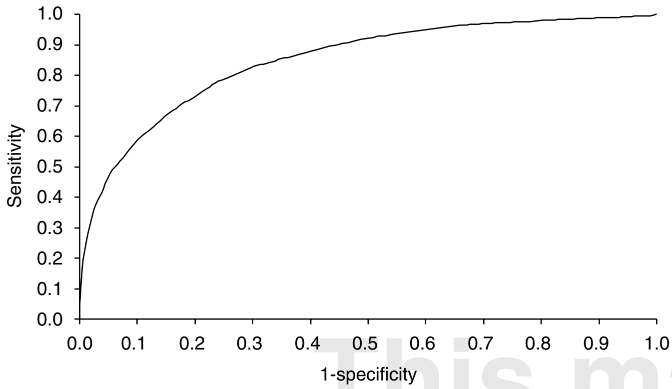

Fig. 2. Top 10% relative operating characteristic curve. The relative operating characteristic curve graphs sensitivity versus specificity. The measurement typically used to evaluate the goodness of this curve is the area under the curve, measured as 0.85 in this figure. A higher arc equates to an area closer to 1, indicating higher accuracy of the model.

Prediction tool (HRP) developed by MEDai utilizes different data sets to predict the following year's consumption on an individual member basis. The results of the HRP are delivered in an On-Line Analytical Processing (OLAP) multidimensional tool. The predictive measure is dollars per member per month at the individual member level. An example of the tool is shown in figure 4.

Many people have looked at high-risk prediction through the use of health risk assessment models. Unfortunately, health risk assessment models have limitations with respect to both participation as well as statistical validity given the bias from the small participation. Most of the time regression models are completed with respect to the health risk assessments.

Different data sets are utilized either individually or in combinations. An example of this would be the use of pharmacy data and professional and facility claims data or both. In fact, models can be built using either of these data sets by themselves or together. In the case of Sentara, all available claims from the core system at the health plan are utilized, as well as pharmaceutical data from the pharmacy claims processor.

6. Predicting Resource Utilization at Sentara

The purpose and endpoint of modeling is to predict resource utilization. At Sentara, these predictions are used in several key areas. The initial and primary considerations evolve around care management. The individuals with the highest predicted resource needs are evaluated for care management interventions. This identification process is critical to disease management programs. The ability to properly identify the members where the maximum benefit of interventions can be demonstrated represents approximately two thirds of the potential benefit, versus the activity itself. When programs are refined to advantage the modeling, success is assured of continuing in all years of operation. The predictions are used specifically to identify several key sub populations discussed in the following sections.

6.1 Identifying Specific Subpopulations

6.1.1 Top 10% Predicted Utilizers

The top 10% predicted utilizers are reviewed. In general, patients not in the top 10% are not actively managed. Combination rules are utilized for identification and management of the at-risk membership. Given limited resources, the average health plan actively manages 1–3% of the membership population. While one could merely identify the top 2% of the population and manage these members, it is better to identify combinations to track across the various services and expertise giving programs improved efficiencies.

6.1.2 Largest Resource Users

Individuals with the largest predicted increase in resource use are identified. The latter measure is referred to as the delta cost. The delta cost is the difference between the prior year cost and the predicted year costs. Those members in the top 10% of predicted costs and whose delta costs exceed $US2000 are placed in a care management strategy specific to the constellation of medical problems the patient has. These predicted members are the most invisible members to the care management team. Often these individuals have neither disease nor high inpatient admission rates or emergency department utilization. The modeling identifies these members as a result of a constellation of pharmacy, demographics and disease claims.

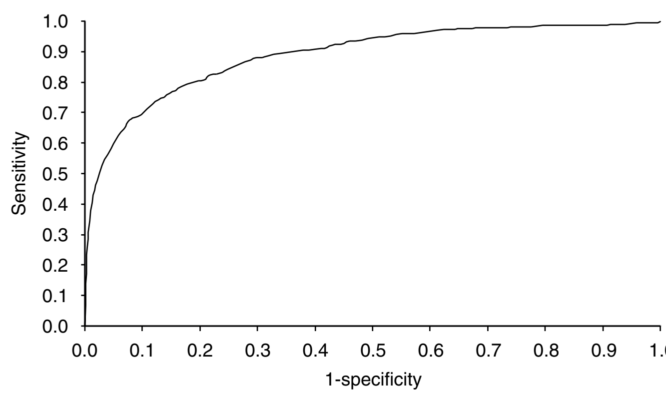

Fig. 3. Top 2% relative operating characteristic (ROC) curve. A perfect model yields an area of 1.0, and a random model yields an area of 0.5. In this artificial intelligence model, ROC area = 0.89.

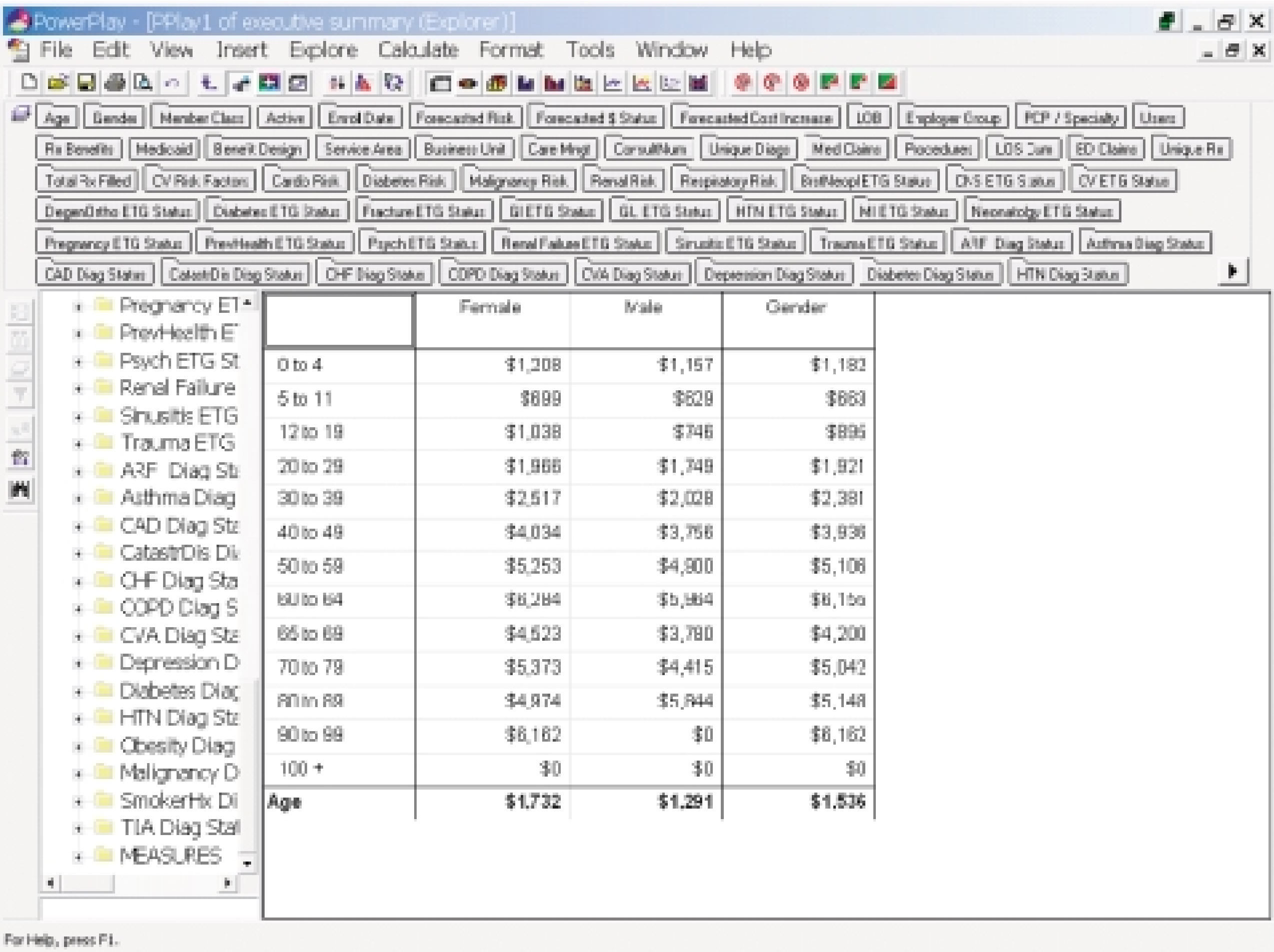

Fig. 4. One result of artificial intelligence predictive modeling is a COGNOS power cube, utilized for data mining and viewing specified statistics on specified dimensions or variables within the data. The example shown is a listing of average predicted cost by gender and age group.

6.1.3 Members with Chronic Diseases

Members with particular chronic diseases and identified in the top 10% predicted for charge utilization are the core group. This approach mirrors Sentara Healthcare's Life Coach[8] programs, including members with diabetes, asthma, chronic obstructive pulmonary disease, schizophrenia and cardiovascular risk. Each program utilizes the list of members that have the 'primary driver' diagnosis and the 'high risk' label from HRP. A life coach is responsible for care management and understanding the individuals' life processes that may influence their healthcare. Examples include financing, transportation, home situation, and family or work stresses. In addition this population is analyzed for patterns around physician providers and demographics. Several life coach programs are centered around the provider and their membership in an effort to augment, enhance and facilitate medical care at the primary points of delivery. These efforts in patient homes or provider offices aligned with HRP yield exceptional clinical and financial results for these populations and the health plan.

Other patients with chronic medical diagnoses in the top 10%, including those with congestive heart failure (CHF), acute and chronic renal failure, and depression, are an additional subgroup. Many of these patients have multiple diagnoses with high predicted resource consumption. Again, patterns are reviewed for physician or demographic groupings. In addition, all four aforementioned subgroups are analyzed for employer and product line patterns to assist underwriting, actuary, sales and marketing.

6.1.4 High Prescription Members

Any patient with eight or more unique prescriptions and 30 total prescriptions in the previous year and in the top 10% is reviewed. In this instance, pharmacists are utilized as life coaches for the purpose of polypharmacy management. Pharmacy utilization carries a very high correlation to future predicted costs (see figure 5). Further data analysis reveals rules utilized to create a

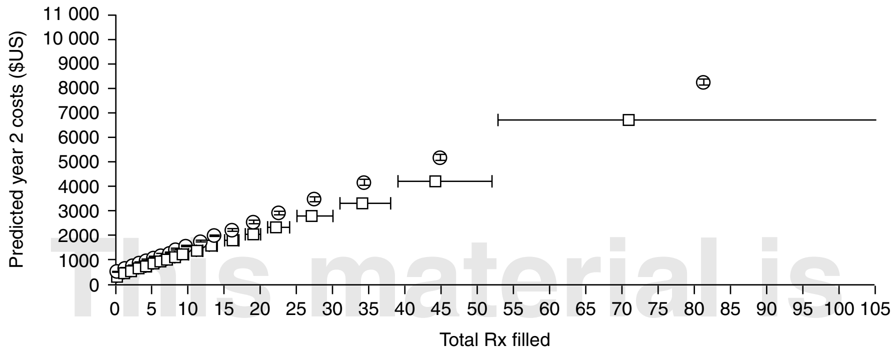

Fig. 5. This graph plots previous year's number of prescriptions (Rx) against next year cost. Due to the noise within the data, a graph of individual members would be indecipherable. Each point on this graph represents the mean X and mean Y for the group of members falling within the range indicated below the data point. The circles graph the means while the squares graph the medians.

'watch list' of members at risk for high resource utilization. One such rule induction is a pharmacy rule. Members with five unique prescriptions and 20 total prescriptions in any 6-month time frame are identified for this 'risk' listing.

6.2 Management of Subpopulations

As discussed in section 6.1.1, a managed care organization only can manage effectively 1–3% of their insured population. Those that attempt to manage a greater percentage are unrealistic as to the resource requirements and outcomes of such endeavors. The use of HRP allows a whole patient approach rather than a specific disease or age group approach to patients and memberships. It allows an understanding of critical relationships between diseases and demographics that may otherwise go unnoticed. How can a health maintenance organization effectively manage all the members with diabetes or CHF that it has? Where should an organization concentrate its resources? Given the knowledge that the predictive model provides, a proactive approach for a care provider maximizes efforts to match the available resources within care management, disease management and the provider community to the needs of the identified population. In addition, Sentara has the capacity to identify sub-populations by practitioner, area, employer, disease state(s), or other key demographics.

After applying the top ten percentile and high delta cost rules to identify some members, Sentara turns attention to specific disease management or life coach programs within the organization. One example of excellent results in Sentara's life coach diabetes program is a 20% reduction in glycosylated hemoglobin (HbA_{1c}) within 6 months in 60 HRP-identified patients in one primary care provider's office. This program has expanded to include nearly 1000 patients with diabetes mellitus with high risk status.

Other uses of HRP include population severity adjustment. HRP creates a case mix index that accounts for benefit design, disease, age, gender, physician and other variables. This severity adjustment is utilized with practitioner reporting throughout at Sentara to adjust the populations within each report. These predicted results offer significant improvements to previously utilized techniques for severity adjusting. The accuracy of this model could improve a capitation reimbursement model.

The tool is packaged into an OLAP application for clinical mining and rules analysis. It allows for disease state or episodic treatment review through diagnosis or Episode Treatment Groups (a methodology of identification and classification of an entire episode of care inclusive of all costs including inpatient and outpatient services developed by Symmetry Health Data Systems; Phoenix, Arizona, USA), patterns of prescribing and cost, outlines of business, employer groups or by primary care or providing physician.

In addition to member identification the cube identifies practitioners with high numbers of the top 10% of the predicted utilizers. This allows recognition of opportunities for care management as well as the potential for assisting practitioners through caring for high risk or highly complex individuals. Data mining rules are identified that lead to earlier high risk tagging for a population. Such rules include numbers of prescriptions, dollars spent on pharmacy, potential high-risk combinations of drugs as well as combinations of diseases and disease management opportunities. Clearly the tool allows recognition of the relationship between disease management and practitioners.

This new knowledge has brought about a realignment of care management within Sentara Healthcare. The redesign and realignment offers several key strategies. The notion of practitioner office-based care management was initiated after identifying high-risk patients. In addition, the HRP recognized the crucial place of pharmacists within care delivery. The entire process has led to a comprehensive approach for care managers at Sentara. The average caseload for our life coach or case manager is double in opportunity costs from previous approaches. This produces a 'multi-million dollar' care manager or life coach. Effectively the resources managed by a single caregiver are double to triple the traditional levels as a result of improved identification.

7. Clinical Reporting at Sentara

For clinical reporting at Sentara, actionable reports are created around the membership and the practitioners. Utilizing the AI models allows very sensitive and highly predictive severity adjustment based on the predicted dollar outcome. In addition, the results have been utilized to model budget and medical expenses. The new information is utilized to identify age, gender and disease-specific patterns, (improving current actuarial tables) or rolling up individual predictions to the employer level. This allows a population view from a severity adjustment standpoint and risk analysis by employer. This technique improves midpoint calculations for actuary modeling.

The entire process clearly has inspired new questions and analysis in underwriting, actuarial service, clinical reporting and care management. Without question the applications of AI technology greatly increased the ability to identify high-risk individuals. Many of the individuals identified were not in case management.

The financial successes of this program still rely on the initiation of improved care and the imagination to modify selected interactions. Clearly the ability to manage high-risk members with respect to their utilization, and the delivery of healthcare services improved. It is difficult to determine the maximum possible accuracy of a high risk prediction model. While advancements continue to be made in AI modeling, there are several kinds of medical outcomes that cannot be predicted based on data that is collected today. Traumas and fractures generally cannot be predicted since they are not caused by a medical history. These kinds of outcomes are examples of why medical outcomes are so difficult, and achieving a 0.34 R^2 in predicting future cost is considered excellent.

A comparison was completed in house between traditional age/gender adjusting and AI methods using calendar year 2000 data. Figure 6 demonstrates these results. Nearly $US25 million was misidentified when using the age-gender groupings as compared to the AI methodology. The age-gender methodology appears to lose accuracy toward the high cost tail of the population, accounting for the majority of the misidentification. The clinical value is clear; identifying individuals and intervening based upon their predicted needs is better than waiting for emergent events or difficulties to surface. This new direction allows for highly predictive and proactive activities to occur within a disease management and care management setting.

8. Conclusion

The future of predictive modeling requires further modeling refinement and subsequent improved levels of accuracy. New variable interactions continue to be discovered, more advanced modeling techniques continue to be applied. New user-interfaces are being designed so users develop a better understanding of the data, and quicker access to the predictive results to improve care delivery and clinical outcomes. Based on this case study of the improvements made at Sentara from using MEDai's HRP, it can be concluded that a high-accuracy predictive model can make a healthcare organization's resources more effective, both clinically and financially.

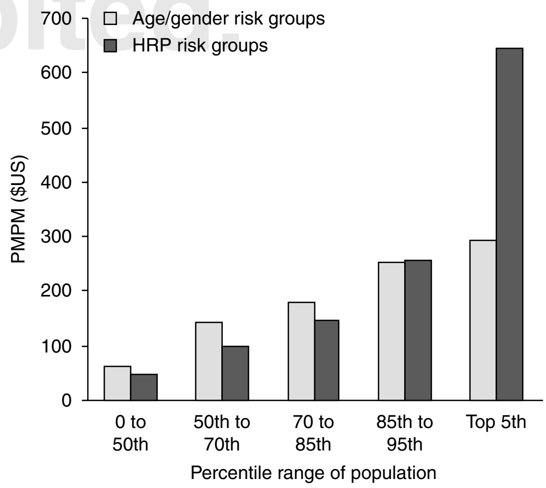

Fig. 6. Comparison of the High Risk Prediction (HRP) tool versus traditional age-gender trend modeling in a commercially (employer based) insured population and the actual per member per month (PMPM) results (in $US) by predicted percentile group for future utilization.

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