Western Oregon
Advanced Health
Coordinated Care Organization

Coos County Oregon

OHP Members: 18,024

Curry County Oregon

OHP Members: 2,707

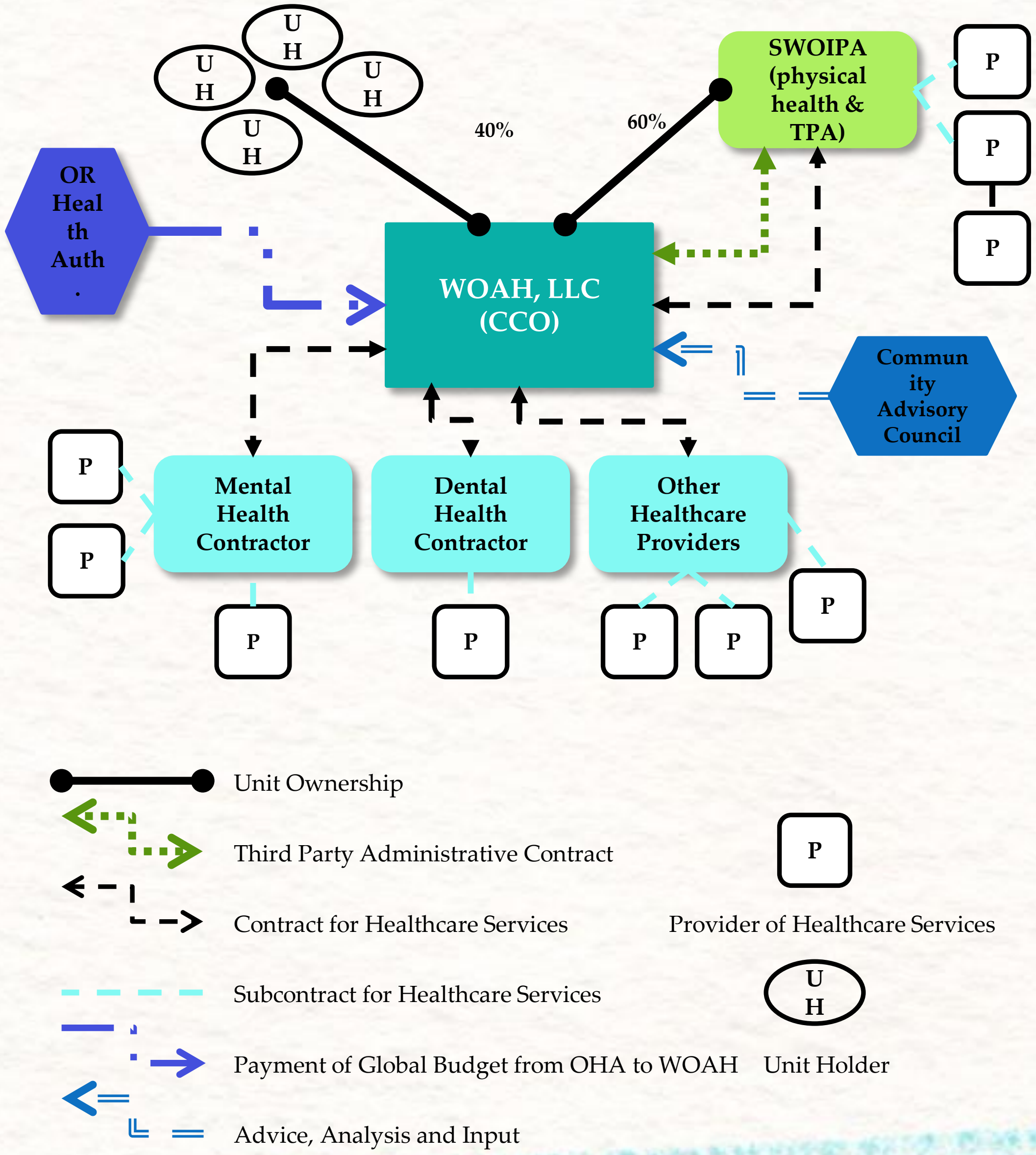
WOAH Board Members

1. Dick Vigue (The Vigue Company)
2. Rajesh Ravuri, M.D. (NBMC)
3. Kathy Laird (Waterfall Community Health)
4. Peter Lund, M.D. (Bay Clinic)
5. Ginger Swan, Coos County Health & Wellness)
6. Laurie Hamilton, D.O. (NBMC)
7. Dennis Zielinski (Coquille Valley Hospital)
8. Aleksandar Curcin, M.D. (SCOA)
9. Gregory Brigham, PhD (Adapt)
10. Dane Smith, D.D.S. (Advantage Dental)
11. Paul Janke (BAH)
12. Dennis Ottemiller, M.D. (Bay Eye Clinic)
13. Melissa Cribbins (Coos County Commissioner)

WOAH Unit Owners

Company Name	Percentage Ownership
South Coast Development, LLC (South Coast Orthopaedic Assoc.)	1.50%
ADAPT	1.50%
Bay Clinic, LLP	2.00%
Coquille Valley Hospital	4.00%
Bay Area Hospital	5.00%
Advantage Community Holding Company (Advantage Dental)	6.00%
North Bend Medical Center	10.00%
Coos County	10.00%
Southwest Oregon IPA, Inc.	60.00%

Figure 1
Western Oregon Advanced Health, LLC
Ownership and Operational Structure



Coos County Community Advisory Committee (CAC)

Name – Position	Name – Position
Anna-Marie Slate, Consumer	David Geels, Member
Jenny Prichard, Consumer	Melissa Cribbins, Member
Linda Hanson, Consumer	Betty Albertson, Member
Linda Morris, Consumer	Bob Lieberman, Member
Margi Lehman, Consumer	Dane Smith, Member
Jason Hedrick, Consumer	Kathy Laird, Member
Sharon Daymond, Consumer	Kelle Little, Member
Patty Savage (Consumer Rep)	Linda Furman-Grile, Member
Renee Menkens (Consumer Rep)	Mike Marchant, Member
Rosemary Bean (Consumer Rep)	Theresa Muday, M.D. WOAH Medical Director

Curry County Community Advisory Committee (CAC)

Name – Position

Mariah B. Bennett, Consumer

Bri Crumley, Consumer

Sharon K. Daymond, Consumer

Rachel Roberts, Consumer

Dori Statton, Peer Recovery Advocate

Patty Savage, RN, Member

Alice Taylor, CNM NP, Member

Theresa Muday, MD WOAH Medical Director

Predicting future healthcare expenses with machine learning

A new approach to population management

Neil Schneider, FSA, MAAA
Arthur L. Wilmes, FSA, MAAA

Milliman

INTRODUCTION

The payment landscape of healthcare is changing from fee-for-service to fee-for-performance. These payment arrangements will shift some or all of the risk to the healthcare provider. As such, providers will need to turn to either existing or new products to manage a patient population and the best process for prioritizing patients within those populations for care management.

Most analytic products in the market focus on ordering patients for care management by highest cost or highest level of morbidity: The sicker they are, the greater the need to manage them. Such approaches may ignore some critical business questions:

- Which patients represent the "greatest risk" under a risk-sharing arrangement?
- Which risks can be mitigated through care management?
- Can advanced metrics be developed to measure care management performance?
- How can the care management process be optimized?

These questions will require analytic approaches more advanced than prioritizing patients with the highest average expense.

MACHINE LEARNING VERSUS TRADITIONAL STATISTICS

With new contracting models, healthcare providers will want to analyze each member in the attributed population to assess what, if any, opportunities for care management may exist. How will this analysis be done? There are a number of analysis techniques in the market that rely upon traditional statistical methods. Traditional statistical methods place importance on data interpretability when defining relationships in the data. These methods result in statistical models where model fit is assessed through hypothesis testing. The result is that traditional analytic tools and regression techniques focus on the average outcome and do not necessarily provide insight into risk that is specific to an individual member. In other words, precision at the level of the individual member is compromised for the sake of improving precision for the average member.

In contrast, solutions based upon machine learning techniques (MLTs) focus on developing models that not only describe the data well but also perform well when making individual outcome predictions. Machine learning algorithms may also be better suited than traditional statistics for healthcare expense predictions. This is due to the number of potential dimensions (variables) involved in data available for analysis.

AVERAGE MEMBER VERSUS INDIVIDUAL OUTLIER

Conventional prospective risk adjusters predict the relative future cost of an average member with given medical attributes. These scores are designed to provide insight into a population's health and expenses but may perform poorly on predicting an individual's expense, which is due to some of the inherent weaknesses of traditional statistics. Such methods also provide no information related to the variability of potential healthcare expense outcomes around the average score or insight into where the best opportunities for improvement in prior performance may reside.

Milliman's approach to predictive analytics focuses on the concept of potentially avoidable healthcare expenses and patients having prospective characteristics with the largest risk for potentially avoidable healthcare expenses.[1] MLTs can be constructed to predict the distribution of an individual's total and potentially avoidable healthcare expenses.[2] Prospective models for the distribution provide insight into a provider's risk per member by not only providing information about the expected healthcare expenses but also attaching values to expenses under adverse outcome scenarios. Understanding an individual's distribution of both total healthcare expenses and potentially avoidable healthcare expenses allow decisions to be made based on the possibility of reducing expenses through changes in the current ambulatory care management. This focus on individual member risk, rather than on overall average population outcomes, gives the healthcare provider valuable information in selecting who and what to manage—in other words, answers to the business questions posed above.

1 Maslow, Katie & Ouslander, MD, Joseph G. (February 2012). Measurement of Potentially Preventable Hospitalizations: Prepared for the Long-Term Quality Alliance, pg. 1.
2 Stranges, E. & Stocks, C. (November 2010). Potentially Preventable Hospitalizations for Acute and Chronic Conditions, 2008. HCUP Statistical Brief #99. Agency for Healthcare Research and Quality.

October 2014

BOOSTING THE INDIVIDUAL SIGNAL - DROWN OUT THE NOISE

Milliman has developed proprietary methods for predicting healthcare expense outcomes utilizing MLT. Variations of Friedman's gradient boosting machine were developed for these predictions.[3] A gradient boosting machine is a framework for creating boosted decision trees. Each decision tree is a simple, interpretable model. A series of true/false decision points lead to predictions for each terminal leaf in the tree.

A single decision tree is not competitive with other models on prediction accuracy; decision trees generally need to be blended to improve the level of accuracy. Boosting is a method of sequentially building small decision trees to slowly build a more robust and accurate prediction. Figure 1 illustrates how predictions are grown from decision trees.

While boosting can often result in dramatic improvements in accuracy, it is at the loss of interpretability and an increased risk of over-fitting.[4] A version of the random subspace method was custom-written for these analytics to reduce the models' over-fitting tendencies and improve computational efficiency.[5]

Random subspacing forces the model to learn from a broader amount of the information, creating trees with more statistical independence. This results in more robust predictions.

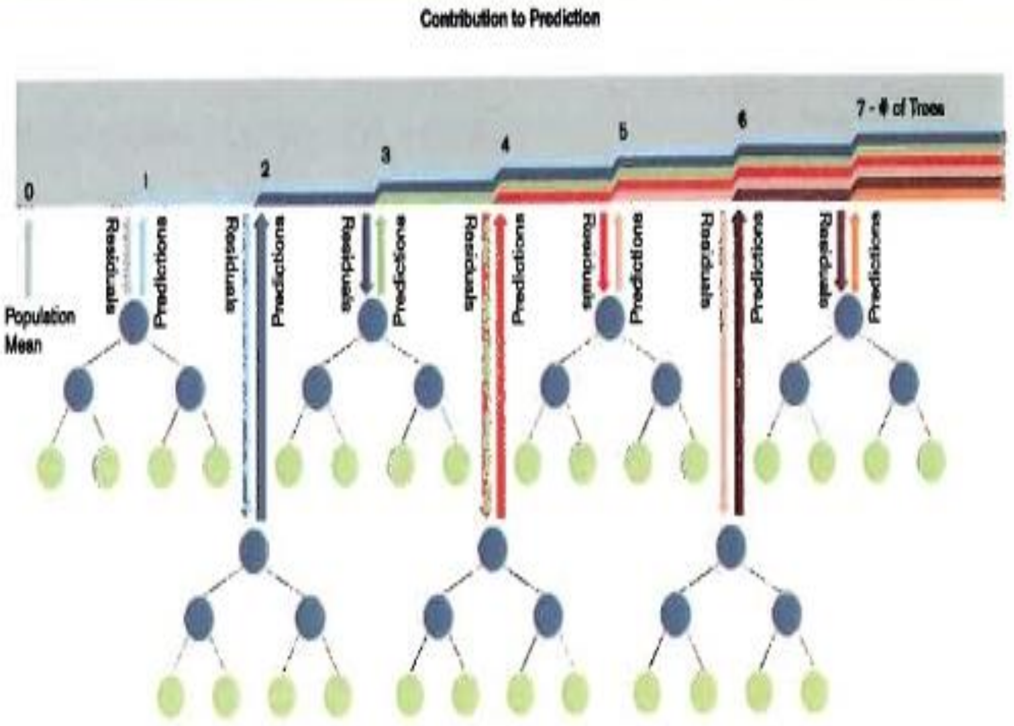
In contrast to other prediction algorithms and methods, gradient boosted decision trees:

- Are more robust against the influence of outlier data
- Reduce the influence of weak or highly collinear variables
- Handle missing values without complex imputations or deletions
- Are designed to model nonlinear relationships and interactions
- Employ multiple regularization techniques to reduce over-fitting

The gradient boosting framework allows for different types of predictions depending on the choice of loss functions to optimize (e.g., probabilities, quantiles, or averages). The appropriate loss functions are chosen to make predictions for the following outcomes:

- *Probability* of an inpatient visit
- *Probability* of an emergency room (ER) visit
- *Potential outlier size* of total healthcare expenses
- *Potential outlier size* of potentially avoidable healthcare expenses

FIGURE 1: BOOSTED DECISION TREES



3 Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics* 29(5):1189-1232.
4 James, G., et al. An Introduction to Statistical Learning: With Applications in R. Springer Texts in Statistics 103, p. 303 DOI 10.1007/978-1-4614-7138-7.
5 Ho, Tin (1998). The Random Subspace Method for Constructing Decision Forests. IEEE Transactions on Pattern Analysis and Machine Intelligence 20 (8): 832–844. doi: 10.1109/34.709601.

The ability of boosted decision trees to produce quality predictions relies on selecting an optimal number of trees. Optimizing the number of trees is done by *k*-fold cross-validation (*k*-fold CV), which involves randomly dividing the set of observations into *k* groups, or *folds*, of approximately equal size. The first fold is treated as a validation set, and a model is built on the remaining $k-1$ folds. The appropriate error metric is then optimized on the validation set. This procedure is repeated *k* times; each time, a different group of observations is treated as a validation set. This process results in *k* estimates of the test error. The *k*-fold CV error is computed by averaging the testing error from each fold.[6] The optimal number of trees is then selected based on the lowest *k*-fold CV error. To improve consistency of the results, the entire *k*-fold cross-validation process is repeated multiple times and the final predictions are averaged. While it is computationally expensive to run all the repeated *k*-folds individually, they are independent models that can be calculated simultaneously with a large computer cluster.

GARBAGE IN, GARBAGE OUT

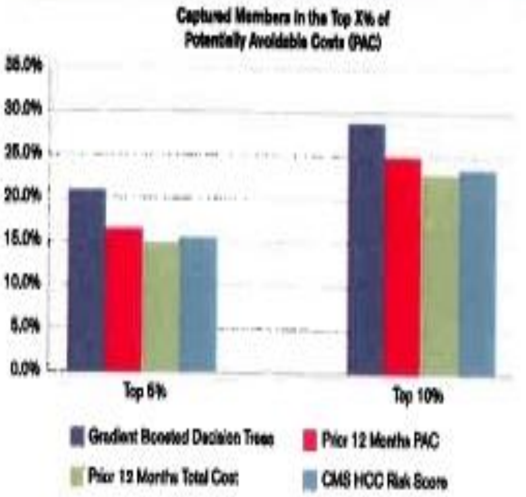
It is important to understand how to best "work your data." The "garbage in, garbage out" adage in this case refers to the need for quality variables to make quality predictions. For example, claim line detail or very specific clinical data is often too granular to make a good model. However, deriving variables from the data will condense the information into useful groups. Summarizing an individual's utilization and costs by month or quarter generally produces better predictive results. With regard to administrative claims and clinical data, the data is generally broken down and summarized into the following categories:

- Demographic information about an individual includes:
  - Gender
  - Age
  - Eligibility status
- Medical conditions: Centers for Medicare and Medicaid Services (CMS) Hierarchical Condition Categories (HCC)
- Risk scores: Varies by line of business
- Historical cost and utilization by:
  - Potentially avoidable services
  - In-network versus out-of-network services
  - Type of service (e.g., inpatient, ER, skilled nursing facility)
  - Date of service
- Electronic medical record data, for example:
  - Vitals signs (e.g., height, weight, and blood pressure)
  - Lab results
  - Smoking status

PERFORMANCE

Predictions of the potentially avoidable healthcare expenses provide healthcare entities with valuable information when selecting individuals for ambulatory management. Historical data is used to make predictions for a known time period. In the Milliman models, we generally predict in six-month prospective increments to isolate on near-term opportunities for additional management. The members within the prediction period are ranked based on their actual potentially avoidable healthcare expenses and then compared to the predicted values. The predictions from the gradient boosting machine are compared with rankings produced from the CMS-HCC community risk scores (for Medicare beneficiaries, for example) and rankings based on the prior 12 months of total and potentially avoidable costs. Figure 2 illustrates the ranking accuracy with the percentage of members in the actual top 5% or 10% who were also identified in the top 5% or 10% of the prediction algorithm.

FIGURE 2: RANKING ACCURACY



CONCLUSION

The advantages of gradient boosted decision trees over traditional predictive modeling techniques help produce more accurate projections of future healthcare expenses. The accuracy can be seen in the improved ranking of members with high potentially avoidable costs. This allows the care coordination teams to strategically target members to manage, saving time and resources—and, hopefully, reaching members before they incur potentially avoidable costs. In aggregate, the algorithm's predictions could ultimately form a basis for benchmarking care management outcomes.

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6 James, G., ibid., p. 181.

The accountable care organization (ACO) represents an entirely new model for healthcare reimbursement. Today's healthcare system must be equal parts insurance company, clinical manager, financial manager, and resource/operations manager. Your ACO management strategy requires a comprehensive approach to population risk management, which is exactly what Milliman PRM offers with its three-dimensional view of data.

Data analytics in three dimensions

Most products in the market focus on ordering patients for care management by highest cost or highest risk. These measures are averages and only approximate expected outcomes over time relative to a comparative benchmark population. They do not provide insight into *actuarial risk* and *actuarial opportunity*, the other two dimensions.

PRM's innovative predictive analytic focuses on actuarial risk and opportunity - the risk of above average healthcare expense outcomes and how care management may reduce that risk. It is one of the first predictive tools to connect the clinical characteristics of the patient with the estimated financial impact that may be derived from the management of that patient – basic business information required for care management decision making.

The PRM difference

PRM is not a factor-driven model. This is an important distinction for PRM as compared to metrics/factors developed from large databases. The former will assign the same metrics/factors to each patient with the same morbidity and demographic composition. However, not all provider institutions and payers have the same level of population management skills or outcomes. PRM can recognize and accommodate these differences, thus providing important insight into efficient healthcare management.

Inside Milliman PRM

Milliman PRM is used by care coordinators, medical directors, physicians, and other professionals who are responsible for population health management. PRM analyzes historic patient data (administrative claims data and clinical data, when available) and, using proprietary predictive models, produces Opportunity Prospective Scores—predicted estimates of a patient's healthcare expenses and utilization over the next six months, absent additional ambulatory management intervention.

The premise for ranking is that patients whose healthcare expense volatility and potential for avoidable costs are the highest should be designated as a priority for additional care management. PRM provides information at the population level and facilitates drill-down to the individual patient level, giving care managers the ability to understand the clinical and non-clinical drivers of potentially avoidable healthcare expenditures for each patient.

Milliman PRM is delivered to each client's end users through a secure hosted web application. Single sign-on capabilities are also available so that PRM can be accessed within a system used by the client.

Learn more

To see a demonstration of Milliman PRM, please contact us at:

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Risk Adjusters, Actuarial Risk, and Predictive Analytics

How are they Related?

Milliman

Neil Schneider, FSA, MAAA
Arthur L. Wilmes, FSA, MAAA

INTRODUCTION

Population management vendors generally suggest stratifying managed populations with risk adjusters to identify the need for care management. Risk Adjusters are commonly suggested as a way to rank patients in order of relative importance. Risk Adjusters have an important role in healthcare cost analytics. They are excellent tools for providing estimates of average expected morbidity value (prospective healthcare expense estimates), can be used to normalize the acuity of a diverse population of patients (for comparative purposes), and are vital to premium alignment (ensuring that premium revenue is aligned with the risk pool being managed).

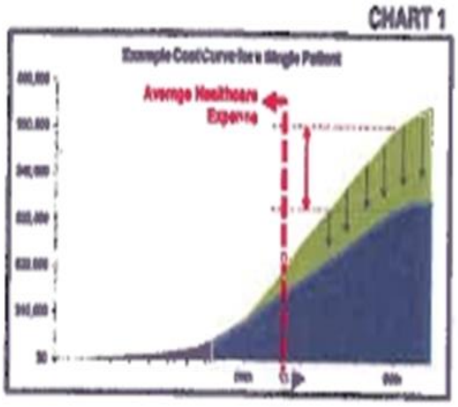
Risk Adjusters, however, are point estimates. They provide limited insight into the actuarial risk associated with each individual patient in the population being managed. Population management requires an analysis of actuarial risk – the risk that actual healthcare expense outcomes will exceed the average expected for an individual patient. Approaches beyond just risk adjusters are needed to understand actuarial risk, and how to manage actuarial risk through the population management process.

RISK ADJUSTERS AND ADVANCED PREDICTIVE ANALYTICS

Risk Adjusters use the term *risk* in their name, but the context of their use is to adjust the risk of different populations such that appropriate average population comparisons can be made. For example, risk adjusters can be uniformly applied to two different populations in order to compare the morbidity burden of one population to the other. These risk adjusted results can then be used to potentially adjust revenue for each population consistent with their relative morbidity burden. Risk factors are also an excellent tool for estimating prospective revenue requirements for a covered population.

Predictive analysis, as presented in Milliman's PRM Analytics™, is focused on actuarial risk, not relative risk. What is the risk that actual healthcare expense outcomes for an individual patient will exceed the average healthcare expenses expected for that patient? Why is predictive analysis necessary? The reason is actuarial risk and how one chooses to manage that risk. Chart 1 illustrates the concept of actuarial risk as it relates to one single patient.

CHART 1



The area in Chart 1 that is blue, plus the area in green, represents the predicted distribution of ordered healthcare expense outcomes (low-to-high) for a specific assigned patient. The area in green represents the portion of the distribution associated with potentially avoidable healthcare expenses. Potentially avoidable healthcare expenses are expenditures for acute services related to chronic conditions that potentially could have been avoided via advanced ambulatory care management. The chart illustrates how the chance for potentially avoidable healthcare expenses emerges in the tail of the distribution (above the 50th percentile). This shows how the Milliman PRM Analytics™ predictive modeling process focuses management attention on healthcare expense volatility, and the amount of volatility associated with potentially avoidable healthcare expenses, rather than average cost. The premise for population stratification is that patients, whose volatility contains the greatest area of potentially avoidable costs, should be the rank order considered for enhanced care management.

The underlying premise for the predictive analytics contained in Milliman PRM Analytics™ lies in the concept of Ambulatory Care Sensitive Conditions (ACSC) http://www.qualitymeasures.ahrq.gov/content.aspx?id=35186. ACSCs are conditions for which aggressive outpatient care and management can potentially prevent the need for hospitalization, emergency department admission, or for which early intervention can prevent complications or more severe disease (AHRQ Quality Indicators—Guide to Prevention Quality Indicators: Hospital Admission for Ambulatory Care Sensitive Conditions. Rockville, MD: Agency for Healthcare Research and Quality, 2001. AHRQ Pub. No. 02-R0203; page 1).

A machine learning process develops an analysis of historic potentially avoidable healthcare expenses associated with ACSC. Retrospective data derived from claims and eligibility data are the basis for historic analysis. Milliman PRM Analytics™ uses this historic learning/analysis to create a predictive model for projecting the distribution of potentially avoidable healthcare expense over the ensuing 6 months. A critical assumption in the predictive models is that no change is made in care management practices and member targeting methods from the historical period. Our experience to date indicates that potentially avoidable healthcare expenses vary by ACO. The variation correlates with the level of care management for each ACO.

Each ACO or payer that we analyze will have unique results. No ACO or payer will have identical values for potentially avoidable care when compared on a morbidity and demographic adjusted basis. This is an important distinction for Milliman PRM Analytics™ as compared to metrics/factors developed from large databases. The latter will assign the same value to populations with the same morbidity and demographics. Not all provider institutions and payers have the same level of population management skills or outcomes. Being able to model those differences based on the population's own data, as done by Milliman PRM Analytics™, is important for efficiently managing populations on an ACO-by-ACO basis.

PRODUCT FUNCTION

The Milliman PRM Analytics™ product provides insight about how to prioritize patients for care management. The product uses proprietary predictive models to estimate the healthcare expenses and utilization in the next six month time period. Patients are initially ranked according to their potentially avoidable healthcare expenses, but can also be ranked based upon any other metric produced in the predictive analytics. An algorithm to identify potentially avoidable healthcare expenditures was developed with machine learning techniques and published retrospective claims research (AHRQ and NYU Center for Health and Public Service Research). The retrospective claims research identifies prior episodes of inpatient admissions and emergency room visits that have a probability to be potentially avoidable. The machine learning techniques provide a prediction as to which patients have a probability for prospective potentially avoidable healthcare expenses. Milliman PRM Analytics™ provides information at the population level and facilitates drill down to the individual patient level allowing care managers the ability to understand the clinical and non-clinical drivers of potentially avoidable healthcare expenses.

INTENDED USERS

Milliman PRM Analytics™ is intended for use by care coordinators, managers of care coordinators, medical directors, physicians, and others who are responsible for population health management. Milliman PRM Analytics™ has utility to health insurance payers, healthcare providers, and employers.

Milliman PRM Analytics™ provides information to supplement experienced and informed clinical judgment. Any clinical decisions remain the responsibility of the clinical managers working in coordination with each individual patient.

DELIVERY METHOD

Milliman PRM Analytics™ is delivered as a web-based application, that is accessed by clients through a secure sign-on process. Access to the tool is not available without a license agreement. Milliman PRM Analytics™, at the user level, does not provide user controlled predictive analytics. Users are limited to view and filter capability through the Milliman PRM Analytics™ interface.

SOURCE OF INTELLECTUAL PROPERTY

The critical intellectual property of the product was developed internally by Milliman professionals. The following components are embedded within this product and are used in whole or in part in the creation of the product.

- Milliman HCG Grouper;
- CMS-HCC Model;
- AHRQ algorithm for historically avoidable cost;
- NYU EDU analysis for potentially avoidable ED utilization;
- AHRQ's Clinical Classification System (CCS);
- MARA (licensed for use within this product).

End users do not have access to these components directly. In some cases, the output of the embedded data or component is visible to the end user through the Milliman PRM Analytics™ interface.

Milliman created a new process to predict potentially avoidable medical costs. We began with the industry standard AHRQ and NYU algorithms for the retrospective identification of avoidable costs. Our clinical staff consolidated and expanded these sources into a comprehensive list that is periodically reviewed and refined. We then combine historic observations with machine learning techniques to train custom predictive models focused on prospective identification of potentially avoidable costs. We employ a careful training strategy to ensure we learn responsibly from the past when trying to predict the future. Our primary learning algorithm is a series of gradient boosting machines, but we are always exploring new opportunities. In our testing and validation work, we have demonstrated improvements over population stratification based upon risk scores or healthcare expense history.

WHY USE MILLIMAN PRM ANALYTICS™?

Current use of this tool in customer settings has resulted in a consistently high level of user satisfaction and increased management efficiency. Specific comments indicative of satisfaction are:

- "It takes me 2 minutes to figure out what to do for a patient when I land on the Conditions and Risk Factors page".
- "I was able to answer a question in 90 seconds when it used to take an analyst 2 weeks to provide me with the data".
- "I don't need to look at the EMR anymore. This has everything I need".
- "This is amazing, the best I have ever seen".

Why use Milliman PRM Analytics™? The reason is actuarial risk and how one chooses to manage that risk.

Neil Schneider, FSA, MAAA, is an actuary with the Indianapolis office of Milliman. Contact him at neil.schneider@milliman.com.

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Credible Physician Performance Rankings

Risk, Credibility, and Actuarially Adjusted Reporting

Neil Schneider, FSA, MAAA
Arthur L. Wilmes, FSA, MAAA

BACKGROUND

Under risk based contracts determining if there is valid difference in healthcare expense performance among participating physicians or physician groups is important. Establishing that some physicians truly perform better or worse than others may provide insight into best practices or other influencers of performance. Complex actuarial adjustments are necessary to identify physicians and physician groups experiencing inferior or superior performance. In this way, practice protocols for high performers may be emulated and poor performers may be remediated.

Understanding if one physician or physician group truly performs better than others can be difficult. Each physician or physician group has a different patient population, different standard of care, and different observed utilization patterns. Methods that *only* risk adjust each physician's healthcare expense data are not sufficient and may lead to inappropriate conclusions.

CREDIBILITY THEORY

The primary problem with physician performance ranking is the implicit assumption that differences among physicians, after risk adjustment, result from differences in performance. Physician performance, no matter how stable, will have variability that needs to be accounted for in any measurement. The healthcare expense data for an individual physician is only a sample of the physician's performance over a short time frame. Like any sample, the data may or may not be "typical" for an individual physician. **Credibility Theory** was developed within actuarial science to better understand (and predict) how a sample of data actually compares to what would generally be typical.

Why are credibility adjustments necessary? Physicians may only have a small number of patients incurring healthcare expenses. Physicians can also have a disproportionate number of catastrophic healthcare expense episodes or a disproportionate number of very low cost healthcare expense episodes. Abnormally high or low costs due to a disproportionate share of episodes can distort the sample average and imply performance that may not be typical for the physician or physician group. Credibility Theory will review sample data characteristics such as the pattern of healthcare expenses and the number of patients served by the physician or physician group. This informs as to how best to adjust the sample of data. The result is a balance between typical healthcare expense experience of a population and the current observed sample.

UNCERTAINTY OF RESULTS

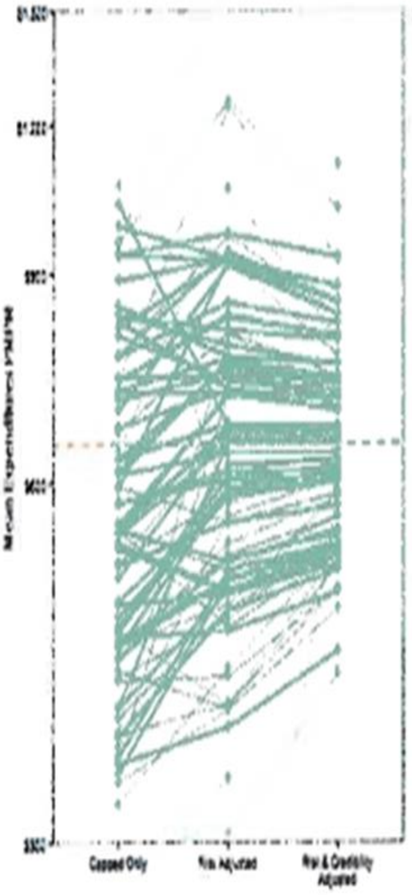
Even in large samples, there will be uncertainty as to whether the average measured from observed data approximates what would be considered typical. A confidence interval is generated around the estimate of the sample average. The typical average for the observed population lies somewhere between the lower and upper bound of the confidence interval. The width of the interval is characterized by a confidence percentage, such as 95%. The percentage is the probability that the confidence interval will include the average typical for the population. Conversely, there is a 5% chance that the typical average will be outside the interval. The more narrow the interval, the more certain the estimate.

The typical average for a physician or physician group is not known for certain. It can only be estimated using the sample of data available. It is not appropriate to make yes/no statements about outperforming a target when that target is a really a blurred region around the typical average. Thus when making comparisons, Milliman expresses the results in terms of the probability that the sample average (after risk and credibility adjustments) will approximate the typical average for the physician or physician group. The yes/no statement of how did this physician perform compared to the typical average is now replaced with a percentage, i.e. it is 80% likely that the physician or physician group has outperformed their typical average.

IMPACT OF RISK AND CREDIBILITY ADJUSTMENTS

Chart 1 uses actual data to illustrate how Risk and Credibility adjustments affect observed sample average health care expenditures (Mean Expenditures PMPM) for a group of individual physicians. Each point on the graph represents an assigned physician's average healthcare expenditures for non-ESRD beneficiaries for the period January 2014 through July 2014 in a Medicare Shared Savings Program (MSSP) ACO. The values are expressed as per member per month (PMPM) expenditure and the chart shows the progression of mean expenditures from observed (capped only), after risk adjustment, and after credibility adjustment.

CHART 1



The horizontal dashed red line at approximately $650 represents the overall best estimate of mean risk & credibility adjusted PMPM expenditures across all physicians. The bolder lines and points represent physicians with more assigned patients. Lighter lines and points represent physicians with fewer assigned patients.

The different vertical lines show the three stages of the risk and credibility adjustment process. (The lines progress from left to right with extreme outlier points beyond the scale of the chart.) The horizontal lines and points illustrate how the mean expenditure PMPM "bends" at each stage of adjustment. The three stages are:

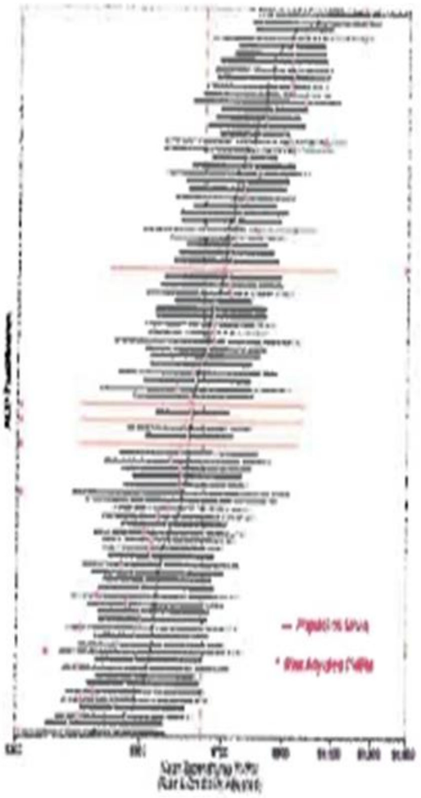
- **Capped Only:** This grouping of values represents the observed sample of mean expenditures per physician. The individual expenditures for each assigned patient have been capped at the 99.9th percentile of aggregate expenditures for the entire patient population. Expenditures are capped to mitigate the influence of outlier claims on the sample average.

- **Risk Adjusted** – Adjustments have been made to the physician's capped PMPM expenditures based on the HCC risk scores of the physician's assigned beneficiaries. The lines between the "Capped Only" stage and the "Risk Adjusted" stage show the impact of risk adjustment on each physician's PMPM expenditures. Risk adjustment can move a physician's PMPM expenditures either upwards or downwards. A risk score greater than 1.00 causes a downward movement while a risk score less than 1.00 causes an upward movement. Note that after risk adjustment, the PMPM expenditures are somewhat more centered on the dashed line, the overall mean.

- **Risk & Credibility Adjusted** - Adjustments have been applied to the physician's capped PMPM expenditures based on the HCC risk scores of the physician's assigned patients and the physician's credibility, which is based on the number of assigned patients and the consistency of expenditures over the period. The lines between the "Risk Adjusted" stage and the "Risk & Credibility Adjusted" stage show the impact of credibility adjustment on each physician's risk adjusted PMPM expenditures. By definition, credibility adjustments will only move a physician's adjusted PMPM expenditures closer to the overall mean; the physicians below the dashed line are adjusted upwards while the physicians above the dashed line are adjusted downwards. Notice that the bolder lines show less movement because these physicians have more credibility. The thinnest lines show adjustments for physicians with little credibility, who therefore are pulled closer to the overall mean. A comparison of the Credibility Adjusted data to the Risk adjusted data shows how a number of physicians may have been inappropriately assigned a materially different estimate.

Chart 2 uses 'Caterpillar Plots' to illustrate the amount of confidence there may be in the individual estimates for Risk and Credibility Adjusted average PMPM expenditures. Each horizontal line on the graph represents a 95% confidence interval for an assigned physician's Risk and Credibility Adjusted average PMPM expenditure. The data is for the same physicians and patients as Chart 1. Each red asterisk shows the physician's average PMPM expenditures after risk adjustment and each green dot shows the physician's best estimate for Risk and Credibility Adjusted average PMPM expenditure. These points correspond with the points on the second and third columns of Chart 1.

CHART 2



The vertical dashed line around $650 represents the overall best estimate of Risk and Credibility Adjusted average PMPM expenditure across all physicians. Notice that the widest intervals tend to have the greatest distance between the red asterisk and the green dot, which displays the impact of the credibility adjustment. For these physicians, the risk-adjusted estimates have low credibility and thus get pulled towards the overall mean. The estimate intervals for these physicians may span several hundred dollars of PMPM as the result of low credibility.

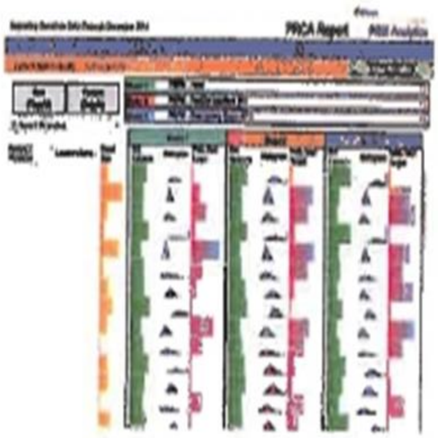
ILLUSTRATING RESULTS FOR PHYSICIANS

The results in Chart 2 illustrate the uncertainty associated with physician performance rankings. The data underlying Chart 2 can be used to create understandable and compelling rankings for physician evaluation. Color coded presentations for physician performance can simplify the understanding of results and still allow for acknowledgement that there remains uncertainty in estimating physician performance.

Chart 3 is an example of physician performance ranking that compares physicians along a number of Risk and Credibility Adjusted population-based efficiency measures such as the following:

- Per Beneficiary Per Month average expenditure,
- Historic potentially avoidable healthcare expenditures,
- Inpatient admission rates per thousand attributed patients,
- Emergency room admission rates per thousand attributed patients, and
- Incurred skilled nursing home days per thousand attributed patients.

CHART 3



The table ranks individual performance by estimating the probability that actual Risk and Credibility Adjusted measures will perform better than a target level of performance assigned to all physicians. The color coding ranges from red to blue with red indicating low probability that a physician will outperform the target. Blue color coding indicates high probability that a physician will outperform the target. Neutral color or white is an indication that a physician has approximately an even chance to outperform the target.

Color coding places the emphasis on the confidence that the individual physician's Risk and Credibility Adjusted result outperforms the target. Numeric values underlie Chart 3, but the data has been replaced with shades of color to increase the amount of information that can be effectively absorbed about the performance of the individual and performance relative to the group. Number views are also available.

Physician performance ranking will continue to grow as a metric for evaluation, especially as data retention capabilities and large health information exchanges efforts also grow. This paper outlined some of the critical issues to be considered when attempting to rank physicians. Advanced techniques discussed herein will improve the credibility of ranking estimates and also improve the credibility and perception by the physicians subject to ranking.

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Western Oregon Advanced Health, LLC

Reporting Based on Data Through September 2014

Demo

Milliman

PRM Analytics

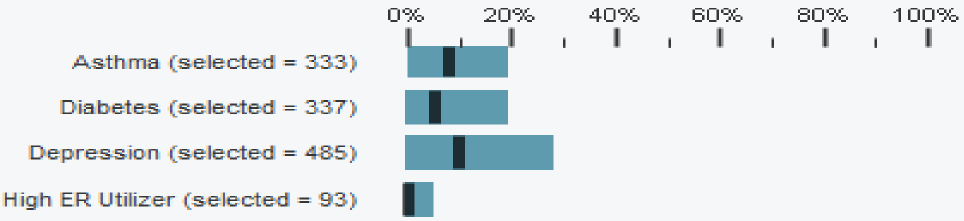
Population Report | Excluded | Patient Profile

Print Unavailable

Filter Population

Patients	
Selected:	1,708
Percentage:	10.0%
Total:	17,077

Prevalence



<< Clear Selections >>

Current Selections

Adverse Scenario P... >90

Search by Member ID or Name

Opportunity Prospective Scores Next 6 Months | Opportunity Historical Scores | Top Clinical Conditions | Clinical Condition Information | Demographic Information | Provider Information

Name	DOB	Probability of Inpatient Admission	Probability of Emergency Room Visit	Adverse Scenario Total Costs Dollars	Adverse Scenario Total Costs Rank	Adverse Scenario Potentially Avoidable Costs Dollars	Adverse Scenario Potentially Avoidable Costs Rank	Prior Month Adverse Scenario Potentially Avoidable Costs Rank
Clark, Ester	04-Jan-1970	17%	18%	$ 58,200	100	$ 3,200	100	
Colletti, Maria	27-Feb-1947	10%	68%	$ 11,500	97	$ 3,200	100	
Kennedy, Cindy	16-Mar-1955	10%	30%	$ 16,200	99	$ 3,200	100	
Robinson, Lula	13-Nov-1990	7%	62%	$ 9,500	95	$ 3,200	100	
Moses, Fern	02-Aug-1962	10%	22%	$ 24,500	100	$ 3,200	100	
Buswell, Kathy	29-Aug-1964	4%	76%	$ 9,100	95	$ 3,100	100	
Mantz, Pamela	04-Sep-1960	4%	55%	$ 13,100	98	$ 3,100	100	
Jones, Aida	10-Jun-1951	9%	36%	$ 17,500	99	$ 3,100	100	
Goodwin, Tamara	22-Mar-1981	13%	63%	$ 9,000	95	$ 3,100	100	
Arthur, Philip	10-Jan-1984	9%	60%	$ 8,900	94	$ 3,100	100	
Pennell, Ron	25-Dec-1964	9%	52%	$ 8,800	94	$ 3,100	100	
Husak, Vesta	27-Jul-1981	3%	73%	$ 8,000	93	$ 3,100	100	
Sprouse, Barbara	08-Dec-1958	5%	68%	$ 10,900	97	$ 3,100	100	
Mosiniak, Yvonne	04-Jun-1990	7%	74%	$ 11,400	97	$ 3,100	100	
Rancourt, Benjamin	17-Jan-1969	6%	41%	$ 13,000	98	$ 3,100	100	
Twilley, Tony	29-Jan-1987	5%	62%	$ 10,500	96	$ 3,100	100	
Silver, Richard	09-Jul-1966	3%	57%	$ 8,700	94	$ 3,100	100	


Western Oregon Advanced Health, LLC
Reporting Based on Data Through April 2015
Milliman
Cost Model Dashboard
PRM Analytics
Filter Cost Model
Filter Population
Current Selections (1): Age Bucket: <1; 1-5; 6-10; 11-15; 16-20
Clear All Filters
Average Monthly Enrollment
PMPM
Utilization / 1,000
Cost per Service
Total Costs
Drill in via Labels
200
180
160
140
120
100
80
60
40
20
0
Q2-2013
Q3-2013
Q4-2013
Q1-2014
Q2-2014
Q3-2014
Q4-2014
Q1-2015
Q2-2015
Total
Time Selection
Q2-2013
Q3-2013
Q4-2013
Q1-2014
Q2-2014
Q3-2014
Q4-2014
Q1-2015
Q2-2015
Summary Statistics
Patients: 14,036 (39%)
Avg Age: 10
Avg Risk Score: 0.47 (0.5x)
Avg PMPM: $141 (0.4x)
Total Costs: $24,962k (19%)
Male/Female Ratio:
Dimensions
Cost Model
Program Description
Clinic
CCO
Report Status
More Dimensions...
Cost Type
Total
Potentially Avoidable
Non-Avoidabl
Time Period
Fixed (Toggle)
Year
Half
Quarter
Month
Line Chart (Toggle)
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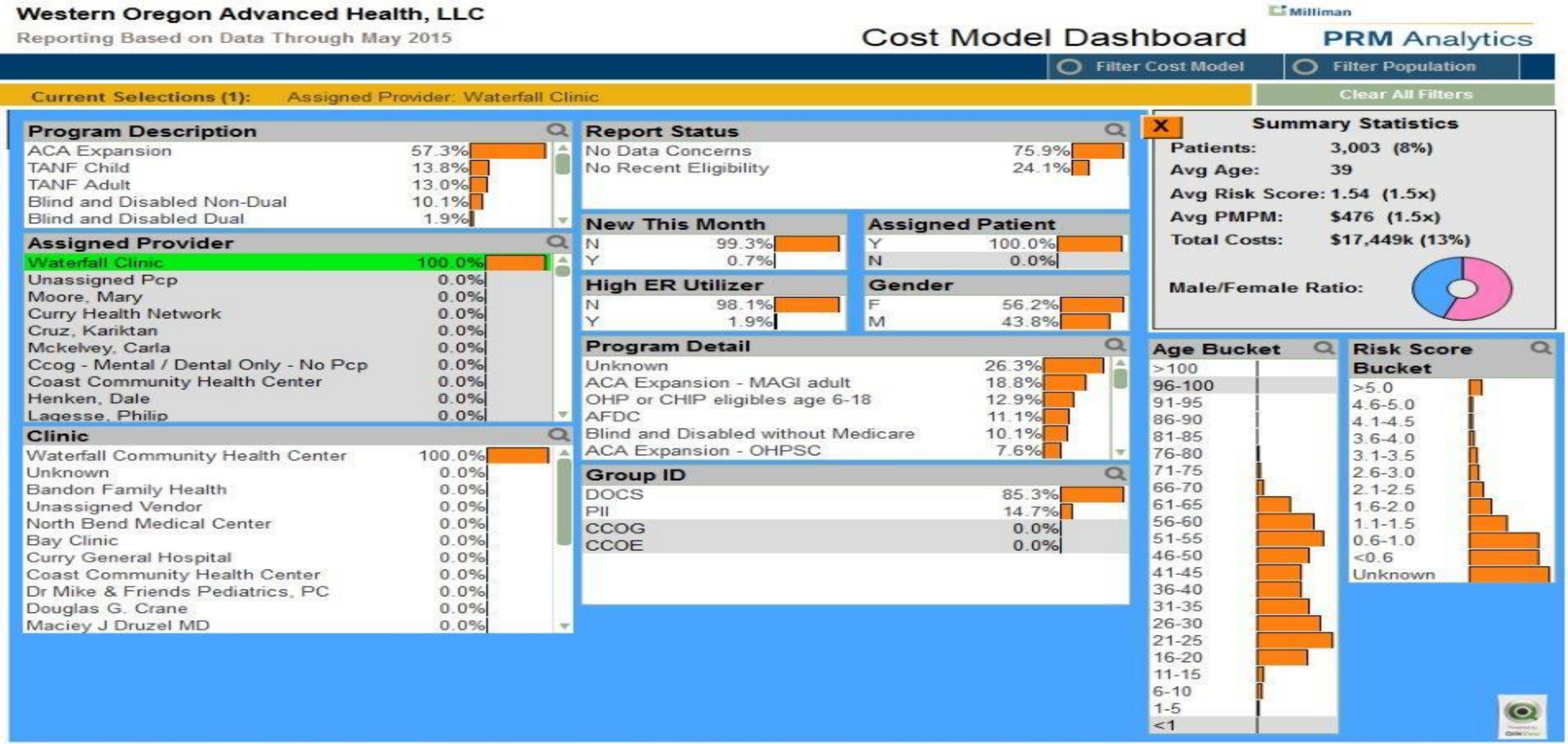
end to benefit or create a legal duty to any third party recipient of its work. In performing the analysis that produced this Milliman PRM Analytics report, Milliman relied on data and other information



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Number of Patients Returned: **772**

Milliman

Care Coordinator Report

PRM Analytics

View Report

Top 10% - Adverse Scenario Potentially Avoidable Costs

New to Top 10%

No Longer in Top 10%

<< Clear Selections >>

Current Selections

Assigned Provider	Coast Commu

Program Description	
ACA Expansion	49.9%
TANF Child	26.0%
TANF Adult	13.0%
Blind and Disabled Non-...	4.7%

New This Month Y N

City, State	
Bandon, OR	69.2%
Port Orford, OR	8.2%
Coquille, OR	6.2%
Coos Bay, OR	3.8%

Zip	
97411	70.2%
97465	8.3%
97423	6.2%
97420	4.3%

Clinic	
Coast Community Health Center	100.0%
Curry General Hospital	0.0%
North Bend Medical Center	0.0%
Bay Clinic	0.0%
Unassigned Vendor	0.0%
Waterfall Community Health Ce...	0.0%
Dr Mike & Friends Pediatrics, PC	0.0%

Assigned Provider	
Coast Community Health Center	100.0%
Curry Health Network	0.0%
Unassigned Pcp	0.0%
Waterfall Clinic	0.0%
Ccog - Mental / Dental Only - N...	0.0%
Zink, Barbara	0.0%
Cruz, Kariktan	0.0%
Henken, Dale	0.0%

Adverse Scenario Potentially Avoidable Costs Rank	
96 - 100	6.0%
91 - 95	6.3%
76 - 90	16.8%
51 - 75	26.4%
26 - 50	24.2%
00 - 25	20.2%

Prior Month Adverse Scenario Potentially Avoidable Costs Rank	
96 - 100	5.3%
91 - 95	5.8%
76 - 90	17.5%
51 - 75	25.6%
26 - 50	24.4%
00 - 25	18.1%
None	3.2%

High ER Utilizer	Y	N
Assigned Patient	Y	N

Search Providers and Services

Probability of Inpatient Admit	
61% - 100%	0.3%
41% - 60%	0.4%
21% - 40%	0.8%
11% - 20%	1.7%
00% - 10%	96.9%

Probability of Emergency Room Visit	
61% - 100%	3.5%
41% - 60%	6.5%
21% - 40%	27.8%
11% - 20%	62.0%
00% - 10%	0.1%

Number of Chronic Conditions	
19+	0.6%
15 - 18	0.5%
11 - 14	2.5%
07 - 10	7.0%
03 - 06	17.4%
00 - 02	72.0%

Chronic Condition			
Asthma	Y	N	New
Diabetes	Y	N	New
Depression	Y	N	New
Psychoses	Y	N	New
CHF	Y	N	New
Back Pain	Y	N	New
COPD	Y	N	New

Clinical Conditions	
Other connective tissue disease- Non-Chronic	15.5%
Essential hypertension	15.3%
Codes related to substance-related disorders- Chronic	15.3%
Other non-traumatic joint disorders- Non-Chronic	14.0%
Depressive disorders- Chronic	12.7%
Anxiety disorders- Chronic	11.8%
Sprains and strains	11.4%

Western Oregon Advanced Health, LLC

Reporting Based on Data Through May 2015

Milliman

Cost Model Dashboard

PRM Analytics

Filter Cost Model | Filter Population

Current Selections (1): Assigned Provider: Coast Community Health Center

Clear All Filters

Program Description

ACA Expansion	44.3%
TANF Child	29.4%
TANF Adult	13.2%
Blind and Disabled Non-Dual	5.2%
Aged Dual	3.0%

Assigned Provider

Coast Community Health Center	100.0%
Ccog - Mental / Dental Only - No Pcp	0.0%
Unassigned Pcp	0.0%
Waterfall Clinic	0.0%
Moore, Mary	0.0%
Curry Health Network	0.0%
Cruz, Kariktan	0.0%
Mckelvey, Carla	0.0%
Henken, Dale	0.0%
Lagesse, Philip	0.0%

Clinic

Coast Community Health Center	100.0%
Bandon Family Health	0.0%
Maciey J Druzel MD	0.0%
Curry General Hospital	0.0%
North Bend Medical Center	0.0%
Bay Clinic	0.0%
Unassigned Vendor	0.0%
Waterfall Community Health Center	0.0%
Dr Mike & Friends Pediatrics, PC	0.0%
Southern Coos Hospital & Hlth Ctr	0.0%
Curry Community Health	0.0%

Report Status

No Data Concerns	74.6%
No Recent Eligibility	25.4%

New This Month

N	98.1%
Y	1.9%

Assigned Patient

Y	100.0%
N	0.0%

High ER Utilizer

N	99.2%
Y	0.8%

Gender

F	56.2%
M	43.8%

Program Detail

OHP or CHIP eligibles age 6-18	21.7%
Unknown	20.7%
ACA Expansion - MAGI adult	11.9%
AFDC	11.7%
OHP or CHIP eligibles age 1-5	6.5%
ACA Expansion - OHPSC	6.0%

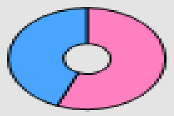
Group ID

DOCS	88.1%
PII	11.9%
CCOG	0.0%
CCOE	0.0%

Summary Statistics

Patients:	1,035 (3%)
Avg Age:	35
Avg Risk Score:	1.15 (1.1x)
Avg PMPM:	$336 (1.1x)
Total Costs:	$4,065k (3%)

Male/Female Ratio:



Age Bucket

>100, 96-100, 91-95, 86-90, 81-85, 76-80, 71-75, 66-70, 61-65, 56-60, 51-55, 46-50, 41-45, 36-40, 31-35, 26-30, 21-25, 16-20, 11-15, 6-10, 1-5, <1

Risk Score Bucket

>5.0, 4.6-5.0, 4.1-4.5, 3.6-4.0, 3.1-3.5, 2.6-3.0, 2.1-2.5, 1.6-2.0, 1.1-1.5, 0.6-1.0, <0.6, Unknown

Western Oregon Advanced Health, LLC

Reporting Based on Data Through May 2015

Milliman

Cost Model Dashboard

PRM Analytics

Filter Cost Model | Filter Population

Current Selections (1): Assigned Provider: 20 of 108

Clear All Filters

Program Description

ACA Expansion	43.8%
TANF Child	21.3%
TANF Adult	17.1%
Blind and Disabled Non-Dual	8.2%
Aged Dual	3.3%

Assigned Provider

Carter, Dallas	8.3%
Sharman, Kent	8.2%
Riccalarsen, Stephanie	7.8%
Mcandrew, Thomas	7.4%
Park, Jonathon	7.0%
Williams, Reginald	6.1%
Keller, Nancy	6.0%
Amavisca, Joseph	5.9%
Millet, Brock	4.8%
Robinson/Millet, Michael	4.5%

Clinic

North Bend Medical Center	93.1%
Bay Clinic	4.0%
Southern Coos Hospital & Hlth Ctr	3.0%
Bandon Family Health	0.0%
Maciey J Druzel MD	0.0%
Unassigned Vendor	0.0%
Waterfall Community Health Center	0.0%
Curry General Hospital	0.0%
Coast Community Health Center	0.0%
Dr Mike & Friends Pediatrics, PC	0.0%
Douglas G. Crane	0.0%

Report Status

No Data Concerns	69.4%
No Recent Eligibility	30.6%

New This Month

N	99.7%
Y	0.3%

Assigned Patient

Y	100.0%
N	0.0%

High ER Utilizer

N	99.4%
Y	0.6%

Gender

F	55.9%
M	44.1%

Program Detail

Unknown	16.8%
OHP or CHIP eligibles age 6-18	16.3%
AFDC	14.4%
ACA Expansion - MAGI adult	14.4%
Blind and Disabled without Medicare	8.2%
ACA Expansion - OHPSC	6.8%

Group ID

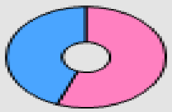
DOCS	83.6%
PII	16.4%
CCOG	0.0%
CCOE	0.0%

X

Summary Statistics

Patients:	6,810 (19%)
Avg Age:	37
Avg Risk Score:	1.19 (1.2x)
Avg PMPM:	$314 (1.0x)
Total Costs:	$28,505k (21%)

Male/Female Ratio:



Age Bucket

>100
96-100
91-95
86-90
81-85
76-80
71-75
66-70
61-65
56-60
51-55
46-50
41-45
36-40
31-35
26-30
21-25
16-20
11-15
6-10
1-5
<1

Risk Score Bucket

>5.0
4.6-5.0
4.1-4.5
3.6-4.0
3.1-3.5
2.6-3.0
2.1-2.5
1.6-2.0
1.1-1.5
0.6-1.0
<0.6
Unknown

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Partnerships In Community:

- Behavioral Health Specialist Embedded in Primary Care.
- Community Wide Collaborative Problem Solving Training.
- Fearsome Clinic.
- Pediatric Crisis Response Project.
- Shared Staffing For High Risk Clients, Care Teams.
- 2 BH Therapist Provide Mental Health Services in Child Welfare Offices.
- School Districts.
- Early Learning Hub
- WOAH Pharmacist and Coos Health & Welfare Psychiatric Nurse Practitioner.

Partnerships in Community:

- Collaboration with Public/Dental Health.
- Penetration Rates for Coos County.
- Behavioral Health Services for Adults – WOAH Through Contract with Coos Health & Welfare.
- Rate for State Hospitalization.
- Behavioral Health Services for Children and Families.
- Transformation Within Our Organization.
- Relationship with Coos County.

Community Wide Collaborative Problem Solving Training

- Attendees Include:
  - Department of Health Services
  - Foster Parents
  - Parents
  - Coos Health & Welfare
  - Bay Area Hospital
  - ADAPT
  - Waterfall school based health services
  - Physicians
  - Juvenile Justice
  - Public Health Schools

Fearsome Clinic:

- Provided twice monthly for children entering foster care.
- Pediatricians, dentists and behavioral health perform assessments in one location instead of children and foster parents having to go to many different locations.

Pediatric Crisis Response Project

- Nearly complete with plan to reduce visits to the ED and hospital admissions for behavioral health concerns in children.
- Committee: WOAH; Dr. Muday, Bay Clinic; Dr. Moore, BAH; Kera Hood & Lisa Rojas, Coos Health & Welfare; Ginger Swan, David Geels, Shawna Schaar, Kairos; Bob Lieberman and John Trapold.
- Project includes building as 24-7 crisis response team for children and families that is mobile in the community and can respond to the family home.
  - Utilize Pony Creek, children's crisis/respite services.
  - Providing skilled trainers and peer supports that can be provided in home during crisis situations.
  - Placing a behavioral specialist in the pediatrician's office.

Shared Staffing for High Risk Clients; Care Team

- WOAH Care Managers and Coos Health & Welfare staff shared clients twice monthly.
- Focus is also on mental health members who are diabetic, weight management, disease management, etc.

2 Behavioral Health Therapists Provide mental health services to the Child Welfare Offices.

- 1 Child Therapist Specialist

- 1 Adult Therapist Specialist

School Districts:

- Coos Health & Welfare places 5 Counselors into various Coos County Schools
  - 2 in Bandon
  - 2 in Coos Bay
  - 1 in North Bend
  - ½ a day at Lighthouse
  - Maslow Project (for homeless youth and their families
- Counselors are available to see any child or family in the school, regardless of insurance coverage
- WOAH is an active member of the Early Learning Hub project

WOAH Pharmacist and Coos Health & Wellness Psychiatric Nurse Practitioner

- Creating partnership to create formulary for mental health medication.
- Both teams are also on the Clinical Advisory Panel.

Collaboration with Public/Dental Health:

- Advantage Dental services provide WIC for infants and their mothers.
  - Also provided at Headstart.
  - Discussion occurring regarding expanding to include dental services in Public Health/Bahavioral Health in clinics for children.
- Ready to Smile program funded by Oregon Community Foundation and facilitated by Coos Health & Welfare.
  - Provides dental screenings, sealants, fluoride varnishes and treatment referrals for all 1st, 2nd, 5th and 6th graders from Reedsport to Brookings.
  - Services will be expanded to include all grades through 8th.

Collaboration with Public/Dental Health:

- Services are available to all children, regardless of insurance coverage.
- Shared expense for the program:
  - Advantage provides the dental hygienists, supplies,
  - Coos Health & Welfare provide the Program Coordinator, van for transportation, and Administrative Staff
  - OCF assists with grant funds and fund raising.

Collaboration with Public/Dental Health:

- CHIP completed and sub-committees created.
  - WOAH active in all sub-committees.
  - WOAH funded VISTA to work on CHIP.
- Targeted case management will be read to move under WOAH when new target date is set.
- Discussions continue regarding possible expansion of home visiting focus to include pediatrician directed nursing services.

Penetration Rates for Coos County

- Data is from 2013 Quarter 3 to 2014 Quarter 2.

	Coos County	State Average
Children Services	9.5%	7.1%
Adult Services	12.8%	13.5%

Rates for State Hospitalizations

	Coos County	State Goal
Hospitalizations	1 Person Per Day	2.5 Persons Per Day

- Attribute Low State Hospitalization to:
  - Coos Crisis Resolution Center (4 beds) for short term crisis stabilization rather than inpatient admission.
    - Facility is staffed 24-7.
    - Admission occurs via ED referral for hospital diversion, member may be referred by CH&W or referral may be used to stabilize following hospitalization.

Development of a 10-Unit Transitional Housing Program

- Program includes a Residential Manager, an Onsite Case Manager (available week-ends and evenings), a CH&W assigned Case Manager and a Medical Provider as needed.
- Program requires the resident to participate in treatment planning to acquire independent living skills and is available to the resident for up to 18 months.
- Residents may move to another set of apartments (6 units) within that complex for semi-independent living or to another 21-unit apartment building for independent living of to community housing.

Behavioral Health Services for Children and Families

- Coos County was the first County in the State to open and operate a crisis/respite facility for children with behavioral health issues.
- In partnership with Child Welfare contracted with the Nurturing Center to provide parenting classes (Nurturing Parenting) to families who are at risk of being opened by Child Welfare.
  - Provide parenting classes, in home skills training and Wrap Around services.
    - Wrap Around services provided with current enrollment of 45 families.
    - Parent-Child Interactive Therapy.

Transformation Within Our Organization

- Quality improvement Committee includes all of WOAH contractors and meets monthly.
- Integration of PH and BH to become Coos Health & Wellness and has led to:
  - Shared staffing between Targeted Case Management staff;
  - Children's Behavioral Health staff;
  - Cross referrals across all organizations;
  - Integrated teams for Quality Improvement;
  - Employee Wellness;
  - Emergency Response.

Relationship With Coos County

- Strong Partnership.
- Coos County is a Share Holder of WOAH.
- Coos County has 2 Members on the WOAH Board of Directors.

3 Quality Measures Performing the Worst

- Depression Screening With Documented Follow-Up Plan
- Adolescent Well Care Visits
- Follow Up After Hospitalization For Mental Illness.

#1 Depression Screening with Documented Follow-Up

- Struggle for Providers to Report
- Various Workflows in Various EHR Systems Do Not Easily Capture Work Being Done
- Providers Have Embraced Depression Screening
  - But depending on EHR/Clinic, most are not successful reporting follow up plan
  - Largest Clinician group over 50% members reported high rate of screening, but scored 0% on recording follow up plan

Resolution for Follow-Up Complications

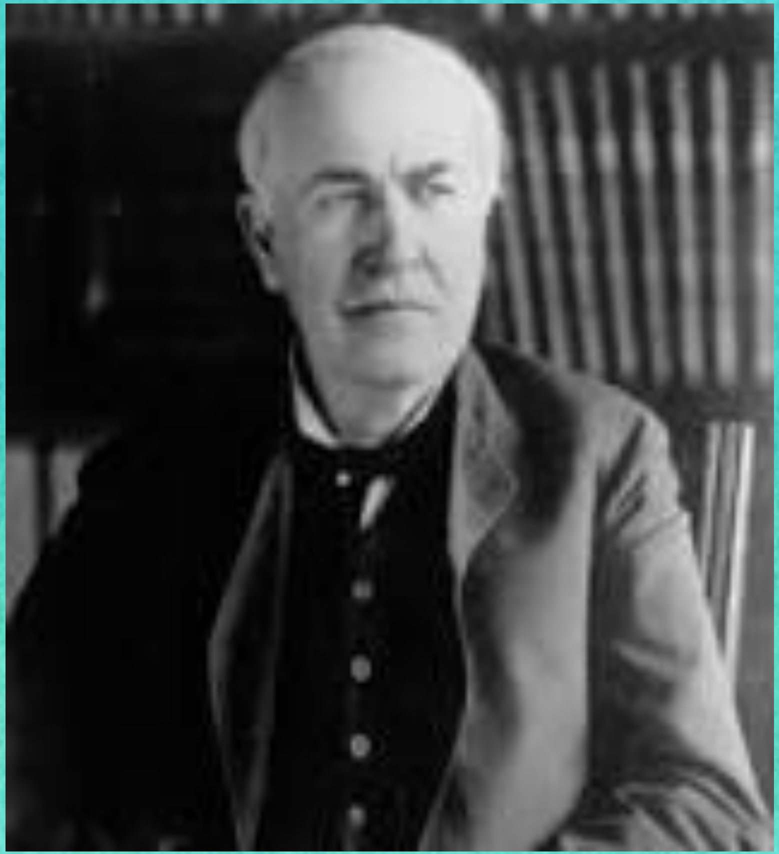
- Milliman has supplied data scientist to understand the nature of how the data is being captured
- Plans to build an interface to give feedback to Providers
- The clinic has changed ist data hosting from offsite to in-house
- WOAH has supported a Quality Improvement Specialist position at clinic that serves as a model for others
- Quality Improvement Specialist serves as an interface between IT and the office to develop workflows that effectively capture the data and doesn’t bog down the clinic

#2 Adolescent Well Care Visits

- Met target in 2013, but missed in 2014
- Engaged group of Pediatricians who have requested WOAH supply them with a list of patients who haven't met the measure
  - Physicians reached out to engage those youth
- Adopted a strategy of turning sports physicals to full-blown health maintenance visits
  - This measure requires that the youth be engaged in their health as well
- Discussing strategies to use local media and other youth organizations to encourage youth to engage with their PCPs

#3 Follow Up After Hospitalization For Mental Illness

- Met benchmark last year, but fell short by 3 follow-ups this year
- Two-Prong Intervention
  - First, data validation led us to find that OHA did not receive some claims that we believed were successfully submitted
    - This led us to re-evaluate our data submission process to ensure reliable submission
  - Second, working to make discharge form the hospital and follow-up with a mental health provider as seamless as possible, even with same-day follow up to engage member during transition



Thomas Edison

Vision

Without

Execution

Is

Hallucination!