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Abstract: Healthcare reform changes everything. Annual and lifetime dollar limits, underwriting, and pre-existing condition exclusion will all be eliminated by 2014. Insurers must offer coverage to any individual regardless of their health status. An overwhelming majority of those who will be mandated to purchase individual insurance is currently uninsured or under-insured. Insurers have insufficient internal data to estimate costs for this new population. A study on how to apply predictive modeling to deal with risks and uncertainties facing healthcare industry in the post-reform marketplace is presented in this article.

Key Words: Predictive Modeling, Health Care Reform, Risk Adjustment, Risk Assessment, Big Data.

INTRODUCTION

As a part of strategy supporting their preparation for healthcare reform, healthcare carriers have been focused on developing high-performance risk models using advanced predictive modeling and data mining criteria to identify new potential opportunities in the post-reform marketplace. The objective is to look for tactics and strategies that can be applied by business units to maximize the margin which is defined as

$$\text{Margin} = \text{Revenue} - \text{Cost}, \tag{1}$$

where, in a generic sense, the revenue represents the amount of money that a health plan expects to receive from the premium charged and the transfer under the risk adjustment, the only permanent program that applies to individual and small group markets under the Patient Protection and Affordable Care Act (PPACA, 2010), or the Affordable Care Act (ACA); and the cost includes the amount of claim liability, the administrative cost, and miscellaneous items. To put it simply, the margin is the difference between the money in and the money out. In order to maximize the margin, health plans must develop business strategies around revenue growth and/or cost reduction. However, strategies implemented for the revenue growth do not necessarily coincide with the cost reduction, and vice versa.

Historically, young and healthy members have been key drivers for profitability in the individual market. Through underwriting, health plans have the ability to know some key information about each person that is insured. The amount of premium collected from a member is the amount of money a plan will earn from that member. The health insurance industry could offer a number of plans to fit everyone's need, and most people insured through individual policies were insured before. Healthcare reform (HCR) is changing everything. Health plans will have to find other ways to learn about their members. The revenue from members will now be more closely connected to their "coded" health status. The number of plans will be limited, and a higher level of benefits is required. There will be a large number of uninsured people entering the healthcare system.

The applications of predictive modeling have grown tremendously in recent years. It provides an advanced analytical framework to help health insurance carriers more accurately develop their business strategies to identify a niche. A useful model provides a disciplined approach for understanding the potential solutions of business problems. These solutions and outcomes give feedback to the original business problems, and the process is continuously refined through ongoing practice. There are two general purposes of fitting a model in healthcare analytics, either predicting the healthcare outcomes or exploring their relationships with various risk factors. When the attention is paid to the latter goal, one can further derive a scoring algorithm by taking the advantage of the systematic component in the model. A scorecard can then be designed for segmenting individuals into different risk groups.

The construction of a specific predictive model depends on the type of healthcare outcome. Exploratory data analysis (EDA) (see Tukey, 1977) can help modelers to identify the underlying distribution of target variable and choose a correct model and link function. When the response variable is normally distributed, linear regression models are often used to describe the linear relationship between the response and a set of risk factors. For a comprehensive review of linear regression analysis, readers are referred to Yan and Su (2009) and Fox (2002).

However, health insurance data are typically non-normal, so an extension of classical linear models is necessary. Generalized linear models (GLM; McCullagh and Nelder, 1989) extend linear models to encompass other types of responses. For example, a Poisson distribution is typically suited for modeling the number of claims over a period of time, a Gamma distribution is usually chosen for modeling the average cost of a claim. Jørgensen and Paes de Souza (1994) introduce the Tweedie distribution, a special member of exponential family, for modeling the pure premium directly. Two other general books on GLM are Dobson and Barnett (2008) and de Jong and Heller (2008).

For modeling binary outcomes, logistic regression and tree-based models (see Breiman, Friedman, Olshen, and Stone, 1984) are popular choices. In addition, there are many other tools such as boosting, random forests, support vector machine, and artificial neural networks that are available for classification problems. For more discussions of these models, one can find Hastie, Tibshirani, and Friedman (2009) very informative.

Regardless of what model is chosen, the goal is to separate "good" risks from "poor" risks and identify positive margin opportunities. In order to identify where the positive margin is, we must understand the revenue received in a risk-adjusted system and the expected cost for future prospects. In short, a risk adjuster is a predictive model in which age, gender, health status, and sometimes other factors are used to determine the amount of revenue redistributed to or from a health plan. The other half of the equation is predicting the claim costs, also referred to as risk assessment or lifestyle-based analytics (LBA). Draaghtel (2011) considers the use of age, gender, and lifestyle characteristics to estimate a prospect's future cost.

This article explains the role of predictive analytics among marketing, revenue programs, and care programs for targeted marketing, revenue growth, and cost reduction, respectively. These three entities can operate independently to achieve their own goals. However, without well-planned coordination, the margin described in (1) may not be optimized. Therefore, it is extremely important to have a dedicated team to monitor and to identify the potential risks. Section 2 gives a brief introduction of healthcare reform. Section 3 shows how a risk adjustment model is used to determine the amount of revenue an insurer will receive in the post-reform marketplace. Section 4 introduces two distinct risk assessment approaches for segmenting prospects. Section 5 discusses the use of predictive modeling focusing on marketing, revenue growth, and cost reduction. Section 6 concludes this article.

HEALTHCARE REFORM

The PPACA was signed into law by President Barack Obama on March 23, 2010. It requires insurers to offer coverage to anyone regardless of an individual's health status, and it eliminates the annual and lifetime dollar limits. However, an overwhelming majority of those who will be mandated to purchase individual insurance are currently uninsured or under-insured. To overcome the uncertainty that concerns pooling and sharing in a new market, on March 11, 2013, the Department of Health and Human Services (HHS) published a final rule on the implementation of the reinsurance, risk corridor, and risk adjustment programs (see Department of Health and Human Services, 2013) to assist health plans with a smoother transition into this new era.

The 3 R's

Just as our elementary school students focus on their 3 R's (reading, 'riting, and 'rithmatic), current health plans are focusing on their 3 R's (Reinsurance, Risk Corridors, and Risk Adjustment) in the post-ACA marketplace. These three programs will have substantial financial impacts on insurance companies and the post-reform marketplace.

The three programs (created in Sections 1341, 1342, and 1343 of the Affordable Care Act) are generally referred to collectively as the "Premium Stabilization" programs since their inclusion was an attempt to prevent "rate shock" in individual and small group market premiums in a post-ACA marketplace.

Reinsurance

The first of the 3 R's is reinsurance. This is a temporary program (2014-2016) that will reimburse insurers who have individual members with high dollar claims. The plans are expected to lower premiums to account for this reduction in claims liability. In 2014, insurers will be reimbursed 80% of member paid claims that exceed $60,000 up to $250,000. Most estimators have placed that to be between 8% and 15% of expected claims.
The total pool to be distributed is $10B for year 2014, which will decrease to $6B for year 2015 and $4B for year 2016. The reinsurance payments will be funded by a Reinsurance Fee of $5.25 per member per month assessed to insurance companies for each member they cover in any line of business they have during year 2014 and will decrease accordingly in subsequent years. Therefore, this effectively makes the reinsurance program a vehicle for non-individual lines of business to subsidize the individual line of business. It makes the products in the individual market less expensive and more attractive to create a better risk pool in the first years of the ACA reforms.

Risk Corridors

The second R is risk corridor, also a temporary program (2014-2016). Modeled after a similar program instituted by the Medicare Modernization Act for the creation of the Medicare Part D pharmacy benefits, it requires plans to share in gains and allows them to be subsidized on losses on "Qualified Health Plans (QHPs)", which are defined as plans that meet the requirements to be sold on the Marketplace. It is applicable for both small group and individual QHP's.

A loss ratio will be calculated on each issuer's experience on non-grandfathered business, considering the impacts of risk adjustment and reinsurance on the same basis as the ACA-required Medical Loss Ratio test. That loss ratio will be compared to a specific target based on the plan's actual administration and profit margin (or loss). If the loss ratio is better than the target by more than 3%, the company will be required to write a check to the government for 50% of the excess. If the loss ratio is better than the target by more than 8%, the company will be required to write a check to the government for 80% of the amount above the 8%, plus 50% between 3% and 8%. The opposite is also in effect, where insurers will receive payment from the government for loss ratios that are above target by more than 3% and 8%, using the same factors.

The risk corridor encouraged plans to price more aggressively for Part D. It was included in ACA since the new market rules, particularly with the guarantee issue requirement, and it may have caused insurers to avoid the market or price conservatively. The historical data will be insufficient to be confidently used to set the premiums appropriately to cover their expected claims. The risk corridor program will expire after three years with the expectation that insurers should then have enough experience to have an adequate foundation for assessing future expected risk.

Risk Adjustment

The final R introduced in ACA is risk adjustment. This is the only permanent program designed to level the impacts of risk selection by enrollees between plans. It creates a risk score for each enrollee in both the individual and small group markets and then facilitates a transfer of money from lower-than-average risk plans to higher-than-average risk plans.

Historically, in underwritten markets, financial success was often determined by risk selection. If you enrolled healthier members and maintained a healthier risk pool, you could charge a lower premium and maintain profitability. That risk selection was under the insurer's control. With the new guaranteed issue requirement, there was concern that the sickest members might disproportionately select a richer plan (or one with more expensive specialists), and that plan would lose money not because they had higher costs or were ineffective, but due to anti-selection from the enrolling population. Risk adjustment is a method to quantify and monetize those risk disparities. It should allow plans to not be concerned about who selects them, but only about doing the best job possible in controlling costs whether through contracting or improving the health status of their enrolled membership.

The risk adjustment program established by ACA separated the individual and small group markets into separate pools. Then, on an annual basis, it scores every member based on the medical diagnosis codes they received during the year in order to calculate the necessary inter-plan transfers to normalize for member risk selection.

HHS-HCC RISK ADJUSTERS

The hierarchical condition category risk adjustment models developed by HHS (HHS-HCC) are predictive models that use the current year diagnoses to predict the current year costs, and are therefore known as concurrent models. This section provides a brief summary of HHS-HCC risk adjustment models. Interested readers can find the HHS Notice of Benefit and Payment Parameters for 2014 (Department of Health and Human Services, 2013) for more information.

HHS establishes 15 risk adjustment models, one for each combination of metal level (platinum, gold, silver, bronze, and catastrophic) and age category (adults, children, and infants). Each HHS risk adjustment model predicts plan liability for an enrollee based on that person's age, sex, and diagnoses (risk factors); thereby, predicting a risk score. HHS proposes separate models for adults, children, and infants to account for cost differences in each of these age groups. The adult and child models are additive; that is, the relative costs assigned to an individual's age, sex, and diagnoses are added together to produce a risk score. Infant risk scores are determined by inclusion in one of 25 mutually exclusive groups based on the infant's maturity and the severity of its diagnoses. If applicable, the risk score is multiplied by a cost-sharing reduction adjustment.

The enrollment-weighted average risk score of all enrollees in a particular risk-adjustment-covered plan within a geographic rating area are then input into the payment transfer formula to determine an issuer's payment or charge for a particular plan.

RISK ASSESSMENT

In this study, we apply two distinct approaches: proxy and build-up (BU). The proxy approach is designed to predict the claim cost as a whole regardless of health conditions, while the BU approach considers a claim cost as a composite of selected condition-specific costs. For both approaches, each risk assessment model is constructed with a two-stage process that consists of a prevalence model and a conditional severity model.

Proxy Approach

The proxy approach considers the claim cost as a whole. It predicts a prospect's future claim cost through the following four steps. To avoid confusion, the final predicted claim cost from any risk assessment model is referred to the risk.

1. The claim cost will be estimated directly several times, and an ensemble model will be deployed to take the average of all possible predictions as the final outcome. That is, with k models built, the risk can be estimated as

$$Risk = \sum_{i=1}^{k} \frac{(Risk)_i}{k} .$$

2. In this study, these identified proxies use, for instance, the cutoffs at the 95th percentile, 90th percentile, 75th percentile, and 50th percentile of PMPM cost in the study sample. For the target variable, which defines the event of interest, individuals with PMPM greater than the cutoff will be flagged as 1 and 0 otherwise.
3. For each proxy, a prevalence model is constructed to predict the likelihood of an individual having the value of 1 or 0 on the target variable. Since the binary target defined in step 2 partitions the sample into two disjoint subsamples, we build a conditional severity model within each subsample. The risk is then determined as the expected cost by conditioning on the values of target variable, providing weights as the corresponding prevalence.
4. A wide variety of proxies were introduced in step 3. They are viewing the problem from different angles. Each model in the collection represents a tremendous amount of work. It is desirable to form an ensemble of these proxies to improve prediction accuracy (see Seni and Elder, 2010). Therefore, the overall risk is obtained using the simple arithmetic average of all proxies as shown in Figure 1.

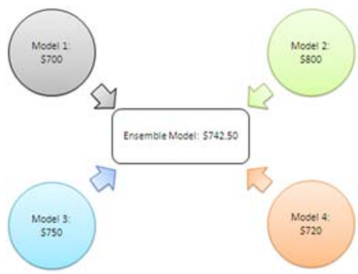

Figure 1: Proxy Ensemble Model

Build-Up Approach

The BU approach, on the other hand, consists of separate prevalence and conditional severity models which are combined to develop an aggregate prediction of claim cost.

1. The BU approach selects a set of medical conditions that are costly and for which LBA is believed to have an impact. A residual category is included to capture costs attributable to all other conditions. With k condition models, the total risk can be estimated by summing over the condition risks as
$$Risk = \sum_{i=1}^{k} (Condition\ Risk)_i .$$
2. In this study, these identified risk conditions include cardiovascular disease, diabetes, hypertension, gastrointestinal disease, and musculoskeletal disease. All of the remaining conditions are combined together to form a residual category.
3. Each condition model consists of two models, a prevalence model and a conditional severity model. The prevalence model predicts the likelihood of a prospect having the condition, and the conditional severity model (severity) predicts the cost of the condition if he or she has the condition. The condition specific risk is then determined by the product of prevalence and severity.
4. The sum of the condition-level predictions results in a total cost prediction shown in Figure 2.

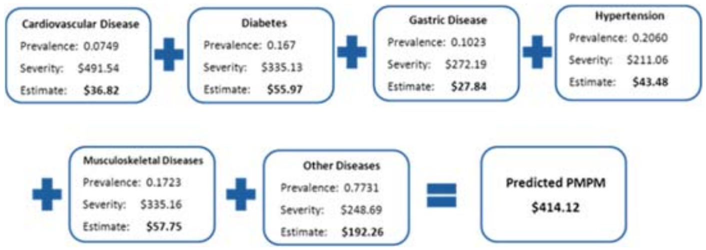

Figure 2: Build-Up Approach

APPLICATIONS

Since the primary goal of marketing is introducing the right product to the right customer at the right time (see Li, Baohong, and Alan, 2011) for the right price at the micro-market level, the role of predictive analytics is to provide data-driven tactics and strategies to answer these questions. The goal of revenue growth, on the other hand, is to focus on increasing the average risk score of a health plan under a risk adjustment payment system. Every additional risk score generated by revenue programs will contribute to the revenue growth in (1). The clinical care perspective is the third crucial component to optimize the margin. By closing the care gaps and eliminating healthcare disparity, patient-centered care programs aim to improve the quality of care and to ultimately reduce the cost of medical care (see Tucker et al., 2011).

Marketing

Long ago and far away in the Far East, a little boy always has his hair cut at the same local barber shop, the VIP Barber Shop. This small barber shop was able to establish relationships with their customers. Over time, those customers became friends, which resulted in happy customers and a profitable business. That little boy grew up and moved away; now has his own family; and is working on predictive analytics in the post-reform marketplace. But one thing has not changed. His mother continues to manage the barber shop and the majority of customers continue to be loyal customers of her shop. Healthcare plans, with millions of customers, cannot form that level of personal relationship with a customer like a local small shop can. They must rely on other ways to connect with their customers. In particular, they can take full advantage of their big data.

The impact of risk modeling, based on the BU approach, can be seen from Table 1, considering a study sample of more than a half million members. After removing the effect of age and gender, the ranked adjusted LBA risk scores from the BU model were used to classify members into LBA 1, LBA 2, and LBA 3 segments.

Loss Ratio	Risk 1	Risk 2	Risk 3	Overall
LBA 1	79%	73%	73%	74%
LBA 2	81%	79%	75%	77%
LBA 3	99%	93%	82%	87%
Overall	87%	82%	77%	80%

Table 1: Loss Ratio Impact of Risk Modeling

Meanwhile, the HHS-HCC risk adjustment algorithm was applied to these members, and Risk 1, Risk 2, and Risk 3 segments were created to indicate the severity of HHS-HCC risk score. Table 1 displays the impact of risk modeling in terms of expected loss ratio. With the consideration of risk adjustment transfer mechanism, a Silver plan with $2,000 deductible, 80% coinsurance, $6,000 out of pocket (OOP) maximum, and an overall 80% loss ratio is assumed throughout this article.

People in LBA 1 and LBA 2 segments are more desirable than those in LBA 3 segment, having the expected loss ratio ranging from 74% to 87%. On the other hand, the HHS-HCC risk segmentation suggests that prospects in

Risk 3 have a loss ratio lower than that of Risk 1 or Risk 2. Table 2 considers the combination of the Proxy and BU approaches, with five risk segments from each model. This ensemble approach is able to provide us the range of loss ratio from 67% to 93%, which is a better risk separation than the single model.

		Proxy					
	Loss Ratio	1	2	3	4	5	Overall
BU	1	67%	75%	77%	82%	79%	73%
	2	69%	73%	77%	80%	88%	76%
	3	68%	73%	73%	80%	83%	76%
	4	70%	83%	79%	82%	83%	81%
	5	85%	81%	89%	90%	93%	90%
	Overall	68%	76%	78%	83%	89%	80%

Table 2: BU and Proxy Ensemble

Revenue Growth

Predictive analytics is essential in revenue programs, where "selective interventions" – finding people and families in need of healthcare – is a must, given only limited resources available to the operational units. The use of predictive analytics is to make the management of revenue more efficient. Member-focused engagement and provider performance profiling are two areas that will benefit from predictive analytics.

The member-focused engagement aims to create a rules engine to improve the quality of care based on in-home or other types of prospective health assessments (see Wilson et al., 2005). The measure of quality is based on accurate medical condition coding, care management, and efficiency. One can develop a statistically credible and focused approach for identifying high-opportunity members for prospective assessments and generating a list of members ranked by the quality of coding accuracy, efficiency, and care management in order to focus the efforts of the revenue programs with regards to member engagement.

These efforts here would include such activities as assuring the company has complete and accurate documentation of a member's health history and health status, using member's status and history to anticipate her/his future health needs and status, using members' status and history to predict the healthcare resources and interventions needed to improve the health of the covered population, and forecasting the revenues under risk adjustment.

Provider performance or practice profiling (see Ash, Shwartz, and Pekoz, 2003) is another avenue to improve the quality of care and to identify additional revenue. Rather than intervene at the member level, the organization can support providers to identify and help populations and their communities to achieve better health. Ultimately, a list of providers will be identified by the accuracy of coding, the quality of care management, and the efficiency in order to focus the efforts of provider engagement.

The potential impact of these efforts can be seen from Table 1 where the expected loss ratio moves from 87% in Risk 1 to 77% in Risk 3. When considering the LBA risk segmentation together with HHS-HCC risk segmentation, the loss ratio is expected to be as low as 73%.

Cost Reduction

With ACA's push for an increased focus on quality outcomes, it is imperative for the organization to increase member-focused engagement strategies. Predictive modeling can help improve care and member outcome and reduce the cost. The healthcare industry is addressing this issue by developing clinical predictive models to prospectively identify members with health needs who could benefit from care management intervention, and prioritizing resources based on stratifying individuals from those with the greatest opportunity for cost reduction to those with the least likelihood (see Tewari et al., 2001).

Together with real-time and fact-checking analyses, predictive modeling gives a broader view of members that reveal their gaps in care, healthcare utilization patterns, laboratory results, and other pertinent information to help provide strategies for health improvement. In addition, an insurance company wants to determine the best approaches for how the clinical care team can interact directly with the identified member population to not only educate them on their current health opportunities, but also to empower the member to take ownership of his/her own health outcomes.

The movement from LBA 3 to LBA 1 as seen in Table 1 indicates the potential opportunity, a decrease of nearly 13% in loss ratio overall to potential decrease of nearly 20% among people in Risk 1 or Risk 2 segments. By year 2017, the two temporary protection programs, risk corridor and reinsurance, will no longer exist. The risk adjustment is the only permanent program that will determine the premium with risk selection for the health plans. Therefore, every plan will bear the risk that is not effectively explained by the risk adjustment payment system in the post-reform marketplace. In the interim, the advantages gained from targeted marketing and revenue program management will decline over time due to the competitiveness of this market and the improvement in coding proficiently. The future success of any health plan will be its ability to reduce the cost of care of its membership in this post-ACA environment.

The enterprise efforts should be dedicated to reduce health care disparities, to enhance health literacy, and to provide culturally and linguistically appropriate services (CLAS) to improve the quality of clinical care and service for members. In summary, an organization will be evaluated on the collection of race, ethnicity, and language data from members, access and availability of language services, practitioner network cultural responsiveness, culturally and linguistically appropriate services programs, and the elimination of healthcare disparities (National Committee for Quality Assurance, 2010).

Ultimately, the healthcare carriers should provide individualized medical approaches along with a framework for identifying the minimum data needed on patient preferences for accurate medical decision making (Hornberger, Habraken, and Bloch, 1995) to their members. The concept is to customize the individual treatment care plans for members. The company must understand the variability of customers. The universal approach will not satisfy all the consumers, especially when they will have increased freedom of choice in purchasing health coverage. The expectation from the consumer will be that they understand the different treatment plans or options that are available to them. As a payer, it will be extremely important to provide the best quality of care utilizing the most efficient approach for these members.

CONCLUSION

For the health insurance industry, the purpose of predictive analytics is to proactively anticipate potential medical needs for all members and to be able to provide appropriate interventions before certain medical conditions develop or surface for these members. A dedicated team will be required to develop the predictive analytics capability that would benefit the company in the long run. The healthcare insurance environment will continue to become a more competitive and customer-oriented business. The knowledge accumulated from an effective advanced analytics team will serve the company in many areas that could impact all the elements of the margin as described in (1).

Predictive analytics allows for quantitative efforts to predict human behavior. In the context of marketing, these efforts have been helpful at “winning customers”. For political election campaign, it benefits those who apply a scientific approach to grass roots outreach. In the context of healthcare, it can help people and communities to achieve better health, increase resources and save lives.

Predictive analytics is ideally suited for a healthcare organization’s emergent business problems that the existing strategies cannot address in an evolving market where the stakes are high. These problems can be solved through advanced analysis of disparate, petabyte-scale, structured, and unstructured data sources to satisfy customers’ needs. The healthcare industry has a number of potential problems when we consider the challenges of targeted marketing, coding accuracy, revenue growth, healthcare disparity, payment integrity, quality of care, healthcare cost reduction, and ultimately personalized care management.

The reputation of advanced analytics in an organization must be founded upon solving these types of complex problems. It starts with a well-scoped process and direct engagement of the end-users. Typically, this works best on new and emerging initiatives that are identified as the top priorities. It aims on building collaborative relationships with all partners as the insurer leverages its data integration platform to help extract value from existing disparate systems, work more collaboratively with internal and external business stakeholders, create specific analytical workflows, and move the carrier from a health insurance company to a healthcare solution company that will be ready to respond to the diverse challenges of a changing marketplace.

REFERENCES

Ash, A.S., Shwartz, M., and Pekoz, E.A. (2003). Comparing Outcomes Across Providers. Risk Adjustment for Measuring Health Care Outcomes 3rd Edition, Chapter 12. Health Administration Press.

Breiman, L., Friedman, J.H., Olshen, R.A., and Stone, C.J. (1984). Classification and Regression Trees. Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software.

de Jong, P. and Heller, G.Z. (2008). Generalized Linear Models for Insurance Data. Cambridge University Press.

Department of Health and Human Services (2013). Patient Protection and Affordable Care Act; HHS Notice of Benefit and Payment Parameters for 2014.

Dobson. A.J. and Barnett, A. (2008). An Introduction to Generalized Linear Models 3rd Edition. CRC Press.

Draaghtel, K. (2011). Predictive Modeling with Consumer Data. The Actuary, October/November, 28-37.

Fox, J. (2002). An R and S-PLUS Companion to Applied Regression. Sage Publications.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). The Elements of Statistical Learning Data Mining, Inference, and Prediction 2nd Edition. Springer.

Hornberger, J., Habraken, H., and Bloch, D.A. (1995). Minimum Data Needed on Patient Preferences for Accurate, Efficient Medical Decision Making. Medical Care, 33, 297-310.

Jørgensen, B. and Paes de Souza, M.C. (1994). Fitting Tweedie's Compound Poisson Model to Insurance Claims Data. Scandinavian Actuarial Journal 1: 69-93.

Li, S., Baohong S., and Alan L.M. (2011). Cross-Selling the Right Product to the Right Customer at the Right Time. Journal of Marketing Research, Vol. 48, No. 4, 683-700.

McCullagh, P. and Nelder, J.A. (1989). Generalized Linear Models 2nd Edition. Chapman and Hall.

National Committee for Quality Assurance. (2010). Multicultural Health Care Standards and Guidelines.

Patient Protection and Affordable Care Act. (2010). Public Law No. 114-148, 124 Stat. 119.

Seni, G. and Elder, J. (2010). Ensemble Methods in Data Mining Improving Accuracy Through Combining Predictions. Morgan & Claypool Publishers.

Tewari, A., Porter, C., Peabody, J., Crawford, E.D., Demers, R., Johnson, C., Wei, J.T., Divine, G.W., O'Donnel, C., Gamito, E.J., and Menon, M. (2001). Predictive Modeling Techniques in Prostate Cancer. Molecular Urology, Vol. 5, Number 4, 147-152.

Tucker, C., Marsiske, M., Rice, K.G., Herman, K., and Nielson, J.J. (2011). Patient-Centered Culturally Sensitive Health Care: Model Testing and Refinement. Health Psychology, Vol. 30, No. 3, 342-350.

Tukey, J. W. (1977). Exploratory Data Analysis. Addison-Wesley.

Wilson, D.H., Consolvo, S., Fishkin, K., Philipose, M. (2005). In-Home Assessment of the Activities of Daily Living of the Elderly. In Extended Abstracts of CHI 2005: HCI Challenges in Health Assessment Workshop, page 2130, Portland, OR, 2005.

Yan, X. and Su, X. (2009). Linear Regression Analysis Theory and Computing. World Scientific.