

# Dynamic Predictive Modeling in Claims Management - Is it a Game Changer?

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## Introduction

There is a buzz in the risk management industry about the use of advanced analytics and predictive modeling to improve the claims management process and ultimately to reduce claim-related costs. Blogs, conference presentations and magazine articles have been talking about the *potential* of predictive modeling for at least 5 years. There are generic articles touting the benefits of predictive modeling, yet its application and benefits to a risk manager remain unclear. Even white papers from reputable independent sources often lack clarity on questions that are pertinent to risk managers in their understanding of this technology and its benefits. While adoption of predictive modeling by national carriers like Zurich and Liberty Mutual have been discussed in the press, they are not focusing on a system that is geared towards the client - the risk manager or in-house claims management staff responsible for loss prevention and cost containment. In this paper we will highlight how the users of RMIS systems can get an added advantage by having predictive modeling capabilities in conjunction with a RMIS system.

In section two of this paper, we define predictive modeling and provide examples of its popular usage in different industries and an overview of different techniques that are commonly used by the practitioners; section three describes the benefits of predictive modeling in conjunction with a RMIS system; section four looks at model evaluation and cost justification for implementing this technology and section five talks about minimum requirements to get started. We conclude by summarizing the key takeaways from this paper.

## Predictive Modeling Technology

In today's challenging environment Risk Managers are tasked with the responsibility of generating positive results while managing very complex claim issues with fewer internal resources and a variety of out sourced cost mitigation services that when used effectively can yield positive results but when used ineffectively can become an additional cost multiplier on claims. For Risk Managers whose claim volume and various responsibilities makes it personally prohibitive to view and manage every claim, predictive modeling can be an optimal tool.

There are many terms used in the industry to denote a technology that helps businesses make data driven decisions and achieve a more favorable outcome. Under the broad umbrella of analytics lie terms such as business intelligence, predictive modeling, statistical analysis, data mining, machine learning, decision algorithms, and business rules. Business intelligence works with historical data and helps users visualize data in a more graphical and user friendly manner by using hyperlinks, drill up and down methods, data segmentation and clustering approaches.

Predictive modeling goes to the next step and anticipates the future so that appropriate action can be taken and resources assigned earlier in the business process in order to try and achieve better outcomes. Some common and highly profitable usage of predictive modeling include optimization of marketing campaigns in retail, credit scoring in financial services, and churn minimization in the telecommunication industry. The uses of predictive modeling in the insurance industry are many and

growing; they include expensive claims management, fraudulent claims detection, reserve setting, underwriting, and retail marketing campaigns.

Traditional statistical analysis is mostly hypothesis driven. Here the analysts and business experts have insight into the business problem and intuitively understand factors likely to be associated with the outcome. They typically work with these pre-defined variables and try to predict the outcome based on the variables available or some derivative of those variables. Linear and logistic regressions are two common statistical techniques and stack up well in many predictive modeling cases. Especially in a classification problem, logistics models are common but have been around for more than 15 years. Data mining on the other hand is mostly driven by algorithms that usually originated from the computer science and artificial intelligence fields. Many of these algorithms do not require *a priori* assumptions about the factors or variables associated with the outcome. These algorithms explore and test iteratively data patterns that are predictive of the outcome and use many learning and test samples to build a good model. Decision trees, artificial neural network, and support vector machines (SVM) are popular data mining and machine learning techniques.

As a risk manager you may not care much about the techniques used to create a deployable model in your operating environment; but you should care that your predictive modeling business partner is experienced in both the statistical and data mining techniques in model creation; and that several models are built and tested before a final model is chosen. Many times no single model is the best but a technique called “Ensemble” is used which combines several high performance models for a given situation. One other important consideration to keep in mind is that many of the models that you build can be improved over time with new claims data and reassessment of model performance.

The concept of “Learning models” is real and must be considered. This concept plainly indicates that existing models needs to be tweaked and the factor coefficients change over time as new data and insights become available. For example, if a model was built from health care data which had very few cases of MRI and CAT scans historically, it most likely will underestimate the current cost of claims. The higher weighting of recent data and incorporation of new data post deployment cannot be overlooked. In our client engagements, we promote the idea of a “Day Zero” and “Day-90” predictive models. The purpose of 90-day model is not as much to reflect a change in data values but to use additional data which becomes available since the first report of injury.

## Benefits of a Predictive Model in Risk Management

While the predicting technology is equally well-suited for risk managers as well as for TPAs and insurance carriers, the usage of a client-specific model is materially different than a model built for a TPA or a Carrier. The TPA/Carrier model is geared more towards reserving accuracy and more efficient assignment of claim resources on high cost claims. These initiatives seldom result in savings passed on to the Client, even if efficiencies are achieved. Secondly, TPAs and carriers do not have all the data needed to create a robust and useful predictive model from the risk management perspective. Their predictive analysis is largely based on the Claim Experience of their book of business. Rarely does it take into consideration the uniqueness of any individual Client.

We believe that the best models are based on a combination of the Client’s claim history along with other elements of client-specific data . Some examples of unique client data are: the client’s unique

work environment, business/safety/return to work culture, supervisor-employee relationship, and demographic/ behavioral characteristics of its employees. Our experience has been that the client-specific model is a *differentiator* because it determines cost drivers in the client’s environment, allows the client to address these drivers not only in the post-loss claim management process, but can also be used to address cost saving opportunities via pre-loss prevention activities as learnings from expensive claims and factors associated with them are fed back in the loss prevention management.

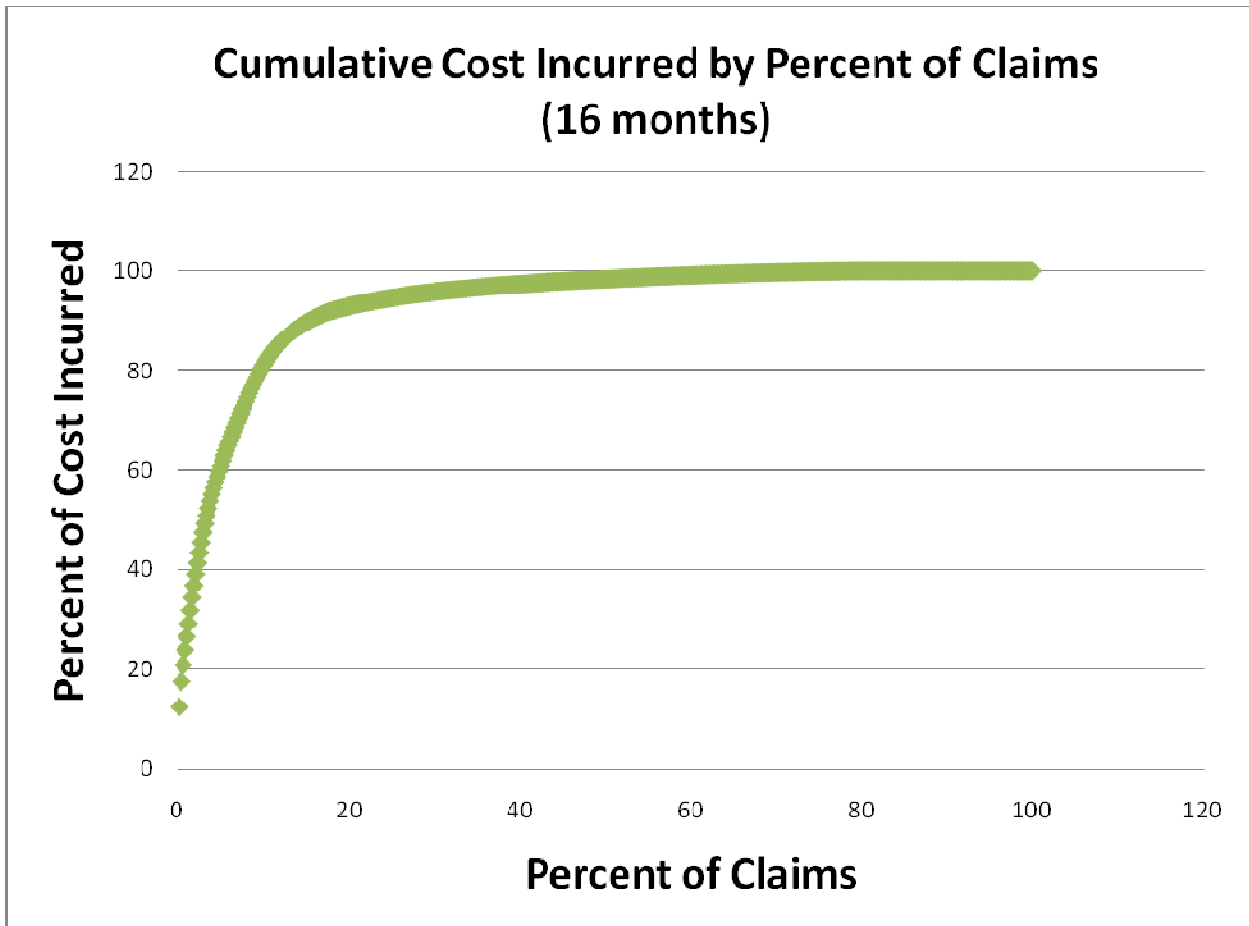


Figure 1

As shown in Figure 1, generally we find that a small number of claims make up a large percentage of the total cost. Thus, the ultimate business objective of a predictive model is to identify these claims early in their development and alert the risk manager. Once a risk manager is alerted of these claims, prompt action can be taken. In brief, a risk manager can benefit from a predictive model by taking multiple actions as follows:

- **Alert Supervisor:** Dynamically alert the Risk Manager and/or In-House Claim Staff of potential high cost claims as new data arises in order to proactively allocate the necessary internal and external resources to effectively manage the cost of the claim.

- **Coordinate with post claim cost control activities with TPA/Carrier:** A dynamic alert of a potentially expensive claim, depending on the information associated with a predictive claim, can result in the assignment of a more experienced adjuster to the case or employment of other cost mitigation resources, such as Nurse Case Management, Physician Peer Review, Surveillance, etc. Predictive modeling can immensely help risk managers keep their TPAs, Insurance carriers, or make the in-house claim staff more effective. Ultimately, it is the client who foots the bill for expensive claims and the miscellaneous post loss costs incurred to manage them
- **Assess Financial Implications:** Have a better sense of reserving and financial liability associated with a given claim. We are not asserting that these claims management activities are not taking place in the organizations today, but often they are brought to bear when it is too late. Predictive modeling provides you actionable information early and warns you of a potentially expensive claim or claims that could turn from medical only to a lost-time claim and go from a minimal reserve to a significant one.
- **Optimize Work Load:** Not all claims are created equal. Thus, when the volume of incoming claims is high relative to the number of people who are available to handle them, a predictive model will bring your attention to 25-30% of the claims that are likely to result in 80% of total cost.

## Ultimate Question: What cost benefits will be derived?

While there are multiple white papers and blogs on predictive modeling in the insurance industry, they very seldom talk about the model's performance and its cost justification from a client's perspective. In this section, we attempt to explain both of these key questions and encourage others to do the same. Currently, predictive modeling technology is in the limelight and a closer scrutiny is essential for the industry to learn and benefit from this technology.

There are multiple ways a predictive model can be evaluated for its accuracy. The two most commonly used methods for classification problems such as identifying expensive or inexpensive claims, fraudulent or non-fraudulent claims are a) an easily understandable 2 X 2 table often termed confusion matrix, as shown in Table 1 and b) an improved version of the same idea presented as a graph called receiver operating curve (ROC) shown in Figure 2. A more practical issue for risk managers is to understand whether savings resulting from the technology is much more than the cost of investment in predictive technology. We will illustrate these key concepts with the help of an example.

Let's assume we have 135 new claims that come in this period in our example, we have made a determination that a claim over \$10,000 is considered to be "expensive" and we have deployed a predictive model that has the following accuracy statistics.

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Table 1: Predicted and Actual Number of Claims at \$10,000 Threshold

Model	Actual Results		Total
<b>Predicted Claims</b>	# of Claims with Value Less than \$10,000	# of Claims with Value Greater than \$10,000	
Claim Value less than \$10,000	82 (True Negative)	18 (False Negative)	100
Claim Value Greater than \$10,000	13 (False Positive)	22 (True Positive)	35
Total	95	40	135

In this example the overall accuracy of the model is (True Positive + True Negative)/Total Claims or  $(82 + 22)/135$  or 77%. Furthermore, the model identified 35 claims to be expensive but only 22 were found to be actually incurring more than \$10,000 for an accuracy of  $22/35 = 63\%$ . Similarly, it had accuracy of  $82/100$  or 82% in correctly identifying less than \$10,000 claims.

Note that the model misclassified or could not identify 18 (False Negative) expensive claims out of a total 40 claims. However, it was remarkable in identifying less than \$10,000 claims for an accuracy of 86% ( $82/95$ ). Also, the model correctly identified 22 / 40 or 55% of the claims that were more than \$10,000. This should not be surprising given that there were almost three times as many inexpensive claims as expensive claims (35 vs. 100) in our hypothetical example and therefore any predictive model would have much higher accuracy rate in identifying inexpensive claims compared to expensive claims. But the ultimate question remains: Is this a good model and would it help a claims management program save money?

The answer will depend upon how much these 40 expensive claims cost you currently and how much additional resources you have to put on 35 claims that were identified as “Expensive Claims.” One employer had an average incurred (at 12 months) of \$25,706 for the top quadrant (most expensive due to high settlement or long term indemnity payments) claims. A potential exists for a 5%-20% reduction in the cost of these claims with the assignment of the best mitigation resources. These resources would typically cost 2% to 4% of the total payout

For first year post-deployment, a cost reduction at the lower end of the range should be targeted. As policy and procedural changes are fully instituted, mitigation resources will become more effective, possibly resulting in cost reductions at the upper end of this range. As a risk manager you should be evaluating both the frequency of claims identified correctly as well as total potential savings by intervening in the predicted expensive claims even though some of those claims are false positive. The potential dollars saved, in fact, would be a more important statistic to review in evaluating the impact of predictive modeling on your claims management program.

The second method of evaluating performance of predictive models is to measure “area under the curve.” This has two advantages over the 2 X 2 table discussed earlier. One, the 2 X 2 table (Table 1) needs a cut-off point or a threshold over which the claims are considered. This is arbitrary and would vary from client to client because you are looking at the performance of the model only at a given threshold. The model performance would have been different if we had the cutoff at \$5000 or at \$20,000 instead of the \$10,000 illustrated in our example. Receiver Operating Curve (ROC) and ‘area

under the curve' eliminates these issues as it shows the performance of the model over a full spectrum of cut-off points. The ROC is created by plotting the proportion of true positives (TP) against the proportion of false positives (FP) at all possible decision thresholds. Furthermore, it compares the model performance to a base line where there is no intelligence and picking an expensive claim is like picking randomly from a hat. Area under the curve (AUC), although a bit involved in its computation, is a good way to measure the quality of a classification model. The AUC varies between 0 and 1. A random model will have an AUC of 0.5 denoted by the 45 degree line in Fig. 2. Most models used in practice have AUC between 0.5 and 1. In general, the larger the area under the curve, the better is your predictive model. This area under the curve is also used to compare different models during the model building and testing process and selecting the best one suited for a given claims management program. ROC also shows the trade-off between true positive and false positive rates as shown in Fig. 2. You can notice that as true positive rate increases, false positive rate increases also. The most optimal cut-off is at a point (shown by arrow) on the curve where the model is able to identify the maximum number of true positive cases and least number of false positive cases.

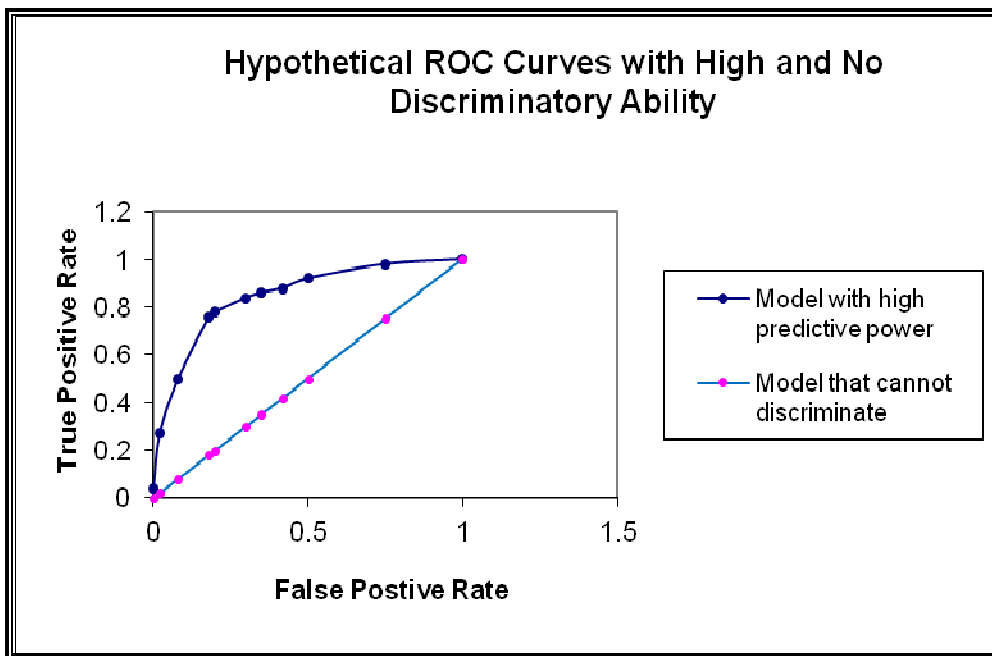


Figure 2. Risk Operating Curve of a good model compared with a random model

As a risk manager, you should also think about *cost of not using the technology*. If there are potential savings of 5% to 20% of total payout per year post-deployment, you should be asking yourself what is my cost of not using this technology with each passing year. Investing in new technologies to increase revenues is exciting and gets much attention. However, equally tangible are savings resulting from a technology such as predictive modeling where a direct dollar for dollar impact can be demonstrated.



## Is My Organization Ready for Predictive Modeling?

Any organization is a good candidate for predictive modeling so long the following three conditions are met:

### **Innovative Culture**

Senior management should be open to try newer technology – as long the cost-benefit analysis makes sense for the organization. For organizations with low claim volume the technology may not be a cost effective solution especially if a risk manager or its existing staff can closely monitor new claims and the development activities of existing claims. You really need a history of 1,500 claims over a three year period and 300-500 new claims per year or else the validity of the model deteriorates too much to be useful. Commissioning a pilot study and review of model performance from prior studies will provide low risk engagement in the process. Any risk manager who has claims cost of more than a million dollars per year should be thinking seriously about leveraging this technology. The cost is not prohibitive and in the range of 1-3% of your annual claims payout depending upon the number of data sources that are integrated in the model building process. The benefits could be in the range of 5%-20% of total payout depending on the distribution of claims cost, current adjustment practices at your TPA, and availability of data to create predictive models.

### **Data**

The effectiveness of the predictive modeling is directly related to the types of data sources available and the quality (data integrity) of the data supplied. As discussed earlier, the best and most robust models are those that are built from your own organizations' claims history, employee socio-demographic history, and other unique employer and/or employee data sources. Your data is best suited for determining true cost drivers in your environment so that remediation techniques have the greatest effect in reducing the financial impact and performance can be tracked to measure progress toward that goal. Although there are no hard-and-fast rules, typically three years of historical data are needed to create an initial model. Deeper history is better, even though more recent data may be weighted more heavily in the modeling process. Multi-year data are necessary to rule out any economic cycle impact, changes in insurance policy, plans, rate, and updates on safety measures instituted on the floor. A consultation with your predictive modeling service provider could help understand the adequacy of your data for implementing this technology.

### **Commitment**

A predictive modeling tool only identifies potential expensive claims and the common factors that these claims may share. In order to optimize the effectiveness of a predictive modeling tool, a risk manager and staff must be committed to act upon the expensive claims identified by the system. Otherwise, you will spend money and there will be no return on your investment. Brokers and consultants can facilitate that process. For example, you can't expect to get better if you do not follow a physician's prescription. However, such non-compliance occurs quite often with individuals and with businesses. The best way to assure compliance is to have your operational staff involved early on in

the decision process. Once you start to see the benefits, you are less likely to go back to the traditional claims management approach.

## Key Takeaways

- The take away message for risk managers, brokers and consultants is that predictive modeling is here to stay and will continue to improve its role in claims management. For some organizations which have the ability to harness data from different sources and allocate the proper resources to potentially “expensive” claims, this technology will be a game changer that could see savings in the range of 5% to 20% of payout and not just bring incremental improvements in claims management.
- In many claims management organizations a small percent of claims incur a large percent of total payments made to claimants. Predictive models can be created to identify this small percent of cases early in their development for faster intervention.
- Proactive organizations are already exploring this technology as evidenced by the sprawling number of articles, blogs, seminars, and industry conference presentations dealing with predictive modeling. This paper provided an overview of predictive technologies, how to evaluate models and what it takes to get started. We focused on the benefits of a predictive model for a risk manager in contrast to benefits and usage of predictive models at a TPA or an insurance carrier. The technology allows a risk manager to keep track of both ends of the problem - work within the organization to improve safety and provide the best services to the injured worker, while monitoring the efficiency and effectiveness with which its TPA or insurance carrier is setting reserves and resolving claims.
- Access to data is a key to success. Using company or client specific data is a differentiator, because it is the best source to identify cost drivers that financially impact your claims. If you have a good database of historical claims and can get access to demographic data of claimants, you have an opportunity to leverage this data in managing claims. Early intervention of a potentially expensive claim is the goal of claims management. Predictive modeling helps us achieve that very goal.
- An intangible benefit of the predictive modeling process is fostering of a culture in the company where data driven decisions prevail. Such a culture results in a strategic advantage for the firm and allows the firm to outcompete the peer firms.