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RIGHT RESOURCES, RIGHT CLAIM: PREDICTIVE MODELING FOR WORKERS COMPENSATION CLAIMS

JIM PAUGH, STEVE LAUDERMILCH, AND FRANK ZIZZAMIA

Predictive modeling applications run behind the scenes, scanning and interpreting thousands of pieces of daily life, affecting the specific mailings we get at our home or office, the pricing of products we buy, the marketing suggestions we receive when we visit certain Web sites — just about everything where money is at stake and making a profit is not something to be left to chance. Predictive modeling is also used in drug efficacy tests to shorten the time to market of a particular drug. A variation called sabermetrics is even used in baseball. How else could one explain how the Boston Red Sox were able to break an 86-year curse?

In the insurance industry, predictive modeling has been used since the mid-1990s in the personal and commercial underwriting process. It affords a segmentation of risk to help identify pricing inefficiencies as well as policies that shouldn't be written or renewed. Modeling has contributed around 4 percent to 6 percent of loss-ratio improvement as well as untold expense reductions.

The time has come for the application of predictive modeling to the arena of workers compensation management. Workers compensation data is rich, disparate, and in need of better management. A basic tenet in claims management is: the earlier the intervention, the better the outcome. Studies have found a window of 60 days following an injury during which a claims professional can have a significant impact on the outcome of a claim. After those 60 days, the injured worker can fall into a disability syndrome that the claims professional will need to fight through before the injury's severity can be managed.

Based on our experience, insurance companies that embark on predictive modeling of claims not only help prevent the disability syndrome but can achieve claim cost savings and improved unallocated loss adjustment expenses (ULAE) performance. Results for self-insurers can be better in both areas (return to work and loss savings) due to their direct control of the work injury situation as well as their direct access to the expanded data sources regarding the injured worker.

THE STRATEGIC VITAL FEW

A quality improvement strategy known as the Pareto Principle holds that only a few factors ("the vital few") are responsible for most of the loss, problem, time spent — whatever the source of difficulty. By bringing to bear many sources of data, predictive modeling applications can identify the vital few.

Let's take an example of three separate workers compensation cases from the same employer. Each case presents itself as a low-back sprain. The first report of injury from each of the cases presents the following information:

Employee A:

- female;
- 38 years old;
- file clerk;
- one prior claim;
- employed six years; and

- being treated by an in-network doctor.

Employee B:

- male;
- 32 years old;
- welder;
- three prior claims;
- employed two years; and
- being treated by an out-of-network doctor.

Employee C:

- male;
- 42 years old;
- mechanic;
- no prior claims;
- employed three years; and
- being treated by an in-network doctor.

Imagine a claims supervisor with the task of assigning these cases to adjusters. To determine the appropriate adjuster for each case, the supervisor needs to take into consideration workflow, the adjusters' present workloads, the complexity of the claims involved, the adjusters' degree of competency, the geographic locations of the claims, and the wants and needs of these employees' employer (the claims operation's customer). Not too long ago, cases were assigned according to alphabetical order.

At first glance, the cases appear straightforward. In-network doctors are being used in two out of the three cases. Two of the individuals are long-term employees. One individual has three prior claims and a short work tenure. Based on this information, the claims supervisor should assign the adjusters as follows: Employee A to the entry-level adjuster; Employee B to the senior-level adjuster; and Employee C to the mid-level adjuster.

However, if additional data about these employees can be brought to light through data mining, we can begin to see how the relative complexity of these three claims changes.

Employee A:

- lives 42 miles from her job;
- married;
- working spouse;
- three children;

- negative financial stability; and
- negative physician treatment pattern.

Employee B:

- lives four miles from his job;
- single;
- lives alone;
- no children;
- positive financial stability; and
- average physician treatment pattern.

Employee C:

- lives 16 miles from his job;
- married;
- unemployed spouse;
- two children;
- average financial stability; and
- positive physician treatment pattern.

With this additional data, it can now be seen that the case assignments originally supposed were all wrong: Employee A needs the fastest and most expert attention, not Employee B. For example, negatively affecting the case for Employee A is financial instability. Perhaps complicating the employee's recovery is that a new car or home was purchased or that a large college tuition payment is due. Add to the mix that she has experienced a negative treatment from her physician, despite being in the network.

In fact, in the arena of medical-only claims, over 5 percent are known to blow up, costing an additional 34 percent. Claim costs and management are inflated beyond appropriate levels due to the medical and behavioral characteristics of the claim.

Identifying claim risk factors from the outset provides meaningful insight into how to most effectively assign and manage claims. Complicating medical factors, such as the presence of comorbidities, misdiagnosis, improper treatment, or overtreatment, as well as the complex nature of a case, are more commonly observed at the middle or later stages of a claim. The presence of comorbidities adds costs and severity to a case if improperly managed. Misdiagnosis may occur at overworked emergency rooms or clinics. Certain health-care providers have a tendency to overtreat. Utilization review can sometimes catch these incidences of overtreatment, but it is an after-the-fact analysis.

The claimant’s behavioral characteristics are by far the most intriguing and biggest drivers of claim severity, even beyond the claim’s medical components. Behavioral characteristics include the claimant’s financial, lifestyle, and occupational circumstances. These characteristics can encompass a person’s penchant for financial risk, attitude toward medical treatment, acceptance of peer pressure from a certain workgroup, job satisfaction, and family pressures. Most claims professionals believe that the severity of a case is truly driven by these behavioral factors, but these factors are typically learned only once the claim is fairly well along.

CLAIMS MODELING: THE TECHNICAL ASPECTS

The process of claims modeling begins with the collection and interpretation of various types of data. Typically called “data mining,” the process utilizes a number of mathematical techniques to analyze large quantities of internal and external data in order to unlock previously unknown and meaningful information about a claimant. Data mining lays the foundation for predictive modeling.

Predictive modeling is the application of data-mining techniques and algorithms to produce a mathematical model that can effectively predict and segment future events. It mathematically compares relationships on a prospective basis between variables and outcomes to determine the importance of such relationships. A sample algorithm or regression analysis would be:

$$\begin{aligned} \text{estimated claim outcome} = & \text{weight}*(\text{Job Class}) + \\ & \text{weight}*(\text{Distance from Employer}) + \text{weight}*(\text{In-Out Network}) \\ & + \text{weight}*(\text{Household Income}) + \text{weight}*(\text{Wage-Workers Com-} \\ & \text{pensation Payment Ratio}) + \text{weight}*(\text{Claimant Age}) \end{aligned}$$

By assigning weights and values to each variable, the algorithm produces a score between 1 and 100.

Hundreds more variables can be added to this analysis. The key, however, is having the data. The most robust claims predictive models do not focus on just one category of characteristics. They include as many as the claims professional’s system has access to — the injury-related medical characteristics, any comorbidities, personality characteristics, and so on.

Here are sample data sources to consider:

- **Internal Data:** claim details, policy data, employer data, pharmacy data, and physician and network data; and

- **External Data:** Dr. Presley Reed's *Medical Disability Advisor*, Occupational Safety and Health Administration, Bureau of Labor Statistics, and American Medical Association.

A large amount of data resides in the notes of the claims adjuster, treating physician, and nurse case manager. Through a technique called "text mining," computer software can identify patterns of certain words as well as key phrases that can be converted into additional variables. By scanning thousands upon thousands of notes, another set of variables can be harvested.

Self-insurers also have large, untapped data sources in employee attendance records, payroll records, production or workflow measures, and performance reviews, to name a few. These data sources can provide deep insight into the work relationship between an employee and his or her supervisor or manager as well as produce the following variables:

- claimant age;
- marital status;
- prescription drug patterns;
- injury date and time;
- existence of a relationship with an attorney;
- changes in treating physician;
- treating physician's specialty;
- whether the treating physician is in-network or out-of-network;
- years of employment;
- salary category;
- whether the claimant is obese or has diabetes or other negative health factors; and
- ratio of average weekly wage to compensation rate.

Each of these variables is weighted and included in the regression analysis. The result or output of the model is called a "score." It allows the claims manager to understand to what degree any particular case, presented with all its variables, has the potential to exceed the expected outcomes.

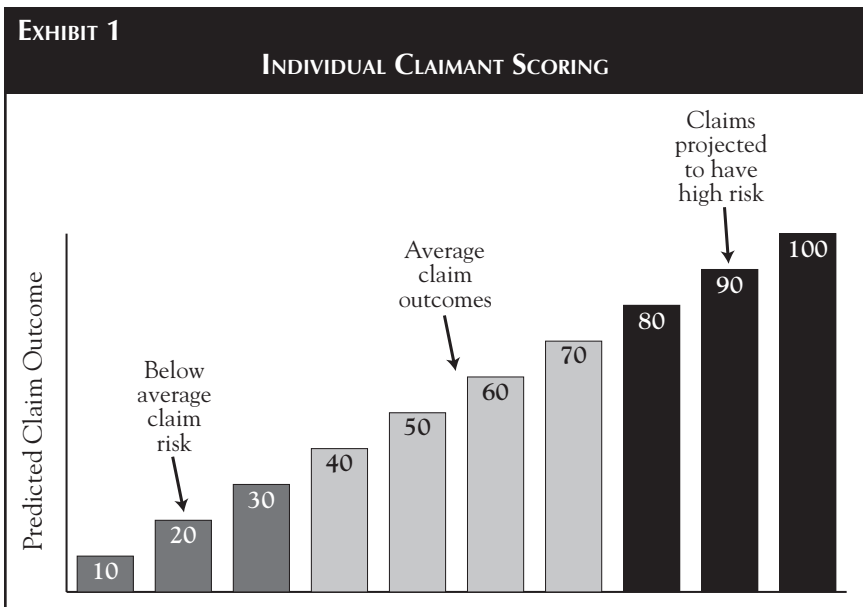
The model produces a score of 1 to 100, indicating the future severity of a particular injury type (see Exhibit 1). The algorithm detects patterns and predicts drivers of outcomes for individual claimants. The score may change over the life of a claim. Typically, the change is for the worse, i.e., as new information is introduced into the formula, a new calculation is

made and the score rises. Practical experience shows that a claim may drift as more information is processed. The biggest scoring shift occurs after the three-point contact (claimant-treating physician-claims adjuster) and as new behavioral variables present themselves.

USING SCIENCE TO CONTROL CLAIMS COSTS

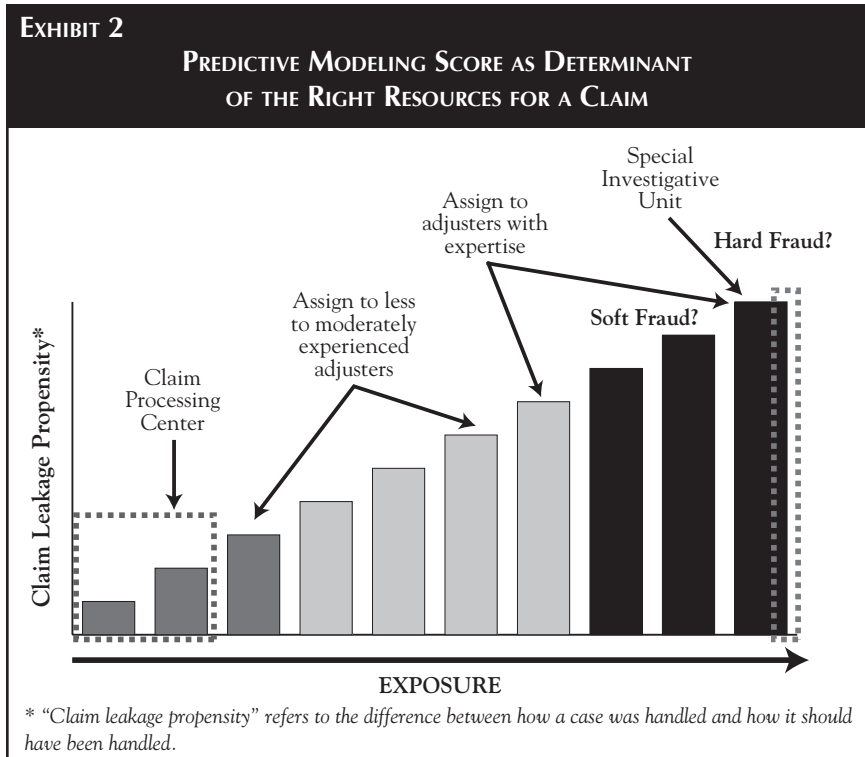
Many claims today are handled using a traditional assignment pattern based on data presented at the first notice of loss. This data includes occupation, date and type of injury, treating physician, and job tenure, for example. Then, based on assimilation of these data and existing business rules (including those dictated by the contract between the claims operation and the client), the claims supervisor will assess for potential risk and assign the claim to a particular adjuster. Three-point contact and reserve setting continue the claims management process and, based upon business rules or intuition, the case may be referred for subrogation, fraud investigation, or medical case management. In the world prior to predictive modeling, this process was developed using trial and error over a period of years.

While the “process” worked, it created many opportunities for so-called “soft fraud.” While it is estimated that 3 percent of all claims involve



deliberate fraud, close to 30 percent or higher are deemed to fall into the category of soft fraud, which can include an injured employee asking a physician for a specific return-to-work date, outright malingering, “conservative” physician treatment patterns, and needless additional physical therapy appointments. Soft fraud can be practiced by injured employees, medical clinics, law firms, employers, and any other entity that touches the system.

By applying the science of predictive modeling, claims operations and self-insurers can evaluate the actual likelihood of soft fraud as a given claim matures. With predictive modeling, the assignment process can be based on a quantitative assessment of the claim that allows for assignment of the right claims to the right adjuster (see Exhibit 2). Modeling can identify cases for autoadjudication, as well as those that will require nurse case management. The difference from the past is that now the behaviors of the claimant can be considered in the equation.



The impact of predictive modeling also extends to adjuster management. First and most obvious is the ability that predictive modeling will provide to set and manage metrics. In the past, normal metrics would be:

- supervisor evaluation;
- claim audit results;
- performance metrics such as closing ratio and provider network penetration;
- client feedback; and
- adjuster's attitude.

Now, with predictive modeling, additional quantitative metrics can be added. Claim outcomes (cost and duration) can be segmented by:

- claim type (auto, general liability, products, workers compensation);
- predictive model score range;
- injury type;
- attorney representation and whether the claim was litigated and settled;
- subrogation potential; and
- industry or class of business.

When coupled with a claim's predictive modeling score, these new metrics allow for the claim's assignment to the right resource, dramatically reducing claim leakage (the difference between actual and appropriate claims handling outcomes).

A predictive modeling system can also offer "reason codes" — short explanations as to why a claim has a particular score. It is recommended that the scores themselves be hidden from the adjuster and that only reason codes be presented. This precludes negative adjuster actions toward the claimant, as the scores should be used only for assignment.

In the sample claim work station screen shot in Exhibit 3, a sample claims triage system presents a score of 92 and provides the key reasons for the rating. The reason codes highlight financial instability, changes in physician, long traveling distance from the employer, and the comorbidity of high blood pressure. Suggested action steps are also provided for efficient triage.

The reason codes along with a claims operation's business rules will dictate what actions should be taken. Some examples are shown in Exhibit 4.

The impact of claims modeling is that it offers many procedural and financial improvements. The actual results will hinge on claims professionals' use of predictive modeling applications and the modification of business rules. (Business rules are developed based upon experience of claims practices. Modification to those rules occurs as new mathematical inferences are found.) Some possible process-oriented improvements include:

- optimally deployed company resources;
- application of established best practices every time;
- standardized triage through automation;
- minimized claim duration balanced with quality of care;
- quicker identification of possible soft fraud;
- quicker identification of potentially explosive medical-only claims;
- better reserving guidance; and
- notice of real-time claim escalation.

EXHIBIT 3

SAMPLE CLAIM WORK STATION SCREEN

Carol Windsor
16 Circle Ave.
Burlington, FL

Claim #: 2006-3456-90807 **Policy #:** 476-05-40-90-0002
Insured: Billings Office Supply, Inc

SIC code: 2752 - Lithographer
Description of Operations: Lithographer specializing in 3 -4 color book/periodical printing

New Data
Employee has changed treating physician
Located 42 miles from work/home
Life Style Risk Indicators
Financial Influencers

Total Reserve: \$24,500

Indemnity: \$14,000

Medical: \$10,500

CLAIM TRIAGE SYSTEM

92

Reason Codes

- Financial Instability
- Change in physician
- >25 miles from employer
- Co-morbidity: High blood pressure

Medical Action Steps:

- Assign to Medical Case Manager
- Obtain medical causal-relationship
- Identify treatment implications of high blood pressure

Adjuster Advisory:

- Obtain recorded statement from claimant
- Increase frequency of claimant contact
- Obtain Medical Case Manager update at next diary

Supervisor Advisory:

- Diary claim for 30 day status review
- Evaluate Special Investigative Unit (SIU) referral

Some possible financial improvements include:

- reduced claim durations;
- lower loss costs per claim;
- improved lump-sum settlements (due to more fact-based decisions);
- reduced loss adjustment expenses;
- increased adjuster productivity; and
- increased customer satisfaction.

While claims predictive modeling is in its infancy, insurers, health-care providers, governmental units, and self-insurers are seeing major improvements and savings. Predictive modeling has positively affected adjuster assignment, identified case settlement ranges, and discovered overpayments, as well as provided many other opportunities for improved claims handling. It is clear that the insurers who are early adopters of this technology will set a new standard for claims management and ultimately help injured workers return to productive lives faster than otherwise.

EXHIBIT 4

**POTENTIAL TRIGGERS TO A HIGH PREDICTIVE MODELING SCORE
AND THE RECOMMENDED CORRESPONDING ACTIONS**

Potential Triggers	Recommended Actions
Claimant receives high exposure score with corresponding “reason codes” suggesting soft fraud (e.g., employee living more than 30 miles from the medical provider and the medical provider and claimant’s attorney located within one mile of each other).	Claims adjuster takes a recorded statement from the claimant and increases the frequency of contact.
Claimant, who is married with children and a working spouse, sustains a June injury, suggesting the possibility of a planned or manufactured injury in time for the children’s summer vacation.	Claim is assigned to a seasoned claims adjuster who has experience with potential soft-fraud cases.
Primary physician has history of treating claims with high severity or visit frequency per injury type (based on International Classification of Disease, Ninth Revision code).	Claim is assigned to a medical case manager to communicate with the provider and monitor treatment.

Jim Paugh is a member of the risk management practice at Deloitte Consulting, where he specializes in postinjury management for workers compensation. Prior to joining Deloitte, he cofounded a national workers compensation consulting firm that served single-site operations as well as Fortune 100 companies. He built the firm to a team of over 50 professionals. Paugh has been a presenter at the Risk and Insurance Management Society's annual conference, the Wharton School, and National Council on Compensation Insurance events. He holds an M.B.A. from Northeastern University in Boston and a B.A. from Assumption College in Worcester, Massachusetts. He works from the Hartford, Connecticut, office and can be reached at jpaugh@deloitte.com.

Steve Laudermilch leads Deloitte's claims consulting practice and has experience working with clients to assess and improve their claims operations and processes. Prior to joining Deloitte, he was a managing director of the brokerage and consulting practice for the Philadelphia office of a global insurance brokerage operation. Laudermilch has held various technical and operational management positions within the property and casualty insurance industry. He holds an M.B.A. from Saint Joseph's University in Philadelphia, a B.A. from Ursinus College in Collegeville, Pennsylvania, and Associate in Risk Management (ARM) and Associate in Claims (AIC) designations. Laudermilch works from the Philadelphia office and can be contacted at slaudermilch@deloitte.com.

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