# Using Your Safety Observations to Predict and Prevent Worksite Injuries

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### Introduction

It seems like a simple question. With enough safety observations, can a safety professional accurately predict a future accident or injury?

The answer is yes—you can do so with an amazingly high level of accuracy. In this paper we will describe how we came to this conclusion through the development of a site scoring method that accurately identifies sites where workers are most at risk based on safety observations alone. This is not intended to be a technical paper. Rather, it is an informal description of our research, the challenges we have overcome and our results to date.

This question is most important for organizations that have many employees, decentralized management systems and multiple sites that exhibit a vast range of unsafe behaviors and conditions. In addition, those most interested in solving this question will likely deal with the diverse traits of the observers collecting this information, including but not limited to, bias, varying perceptions and a wide range of safety knowledge or competencies.

It is obvious that if we increase the time qualified people have to focus on error-prone situations or high-risk work areas, we are more likely to avoid human error, accidents and injuries. Just as an accurate weather forecast enables a farmer to plan and prepare for imminent foul weather, a safety professional benefits from as much time as possible to educate, coach and provide resources for avoiding catastrophic loss.

Before tackling this question, we had to address three big challenges. The first was how to get a large enough data set to ensure the reliability of information. We then needed to determine which variables would be most indicative of risk. Finally, we were concerned with the quality of an observation and specifically, how we could maximize the objectivity of our information.

## Addressing challenges within the observation data

For our research, twelve different customers shared their inspection, observation<sup>1</sup> and loss information from 1424 different sites (with each site having at least five inspections). Over ten million observations were collected, of which about one million were unsafe observations. On average, less than 15% of the sites had any accidents or injuries to report. From a data collection point of view, the observation lists were not exactly the same but all contained elements of unsafe behaviors and conditions (see Exhibit 1 for a sample list). Because the observations were collected electronically on site using DBO<sup>2</sup> SafetyNet,<sup>2</sup> this enabled convenient access and analysis for conducting research.



Exhibit 1. Sample observation list.

Armed with this data set, the next question became which variables were going to present the best indicator of risk. For example, is the number of observers more important than the number of unsafe observations? Is the severity of an observation more noteworthy when it is marked by a safety professional rather than a non-safety professional? To be as comprehensive as possible, our research mandated that we test thousands of variables and millions of combinations of these variables.

We grouped and tested our variables across a broad range of categories which included time (i.e.: days, weeks, months, rate of change between time-based events); unsafe or "at-risk" observations (i.e.: frequencies, percentages and unsafes per inspection); safe or compliant

<sup>&</sup>lt;sup>1</sup> In this paper, the term **inspection** refers to an entire audit, which may be comprised of any number of observations. An **observation** is a specific condition or behavior that is noted by an inspector.

 $<sup>^{2}</sup>$  The data for this study was collected using DBO<sup>2</sup> SafetyNet, which simplifies the collection, distribution and analysis of safety observations.

observations (i.e.: frequencies, percentages and safes per inspection); and people (i.e.: role of inspector and the timing, frequency and history of their inspections). See Table 2 for a sample of variables considered. We then looked for differences between groups of observers and/or differences over time. For example, we wanted to know if it is significant when a safety professional finds an *increasing* number of unsafe observations when a non-safety professional finds a *decreasing* number of unsafe observations on the same jobsite.

Safety Variables		
Total Number of Inspectors	Unsafe Observations in Month One	
Total Inspections Per Month	Safe Observations in Month One	
Monthly Total of High Severity Observations	Weighted Moving Average of Inspection Totals	
Monthly Total of Safe Observations	Percent of Observations Done in the AM	
Monthly Total of Unsafe Observations	Percentage of Sub Categories Inspected	
Average Percent of Items Inspected on Other	Housekeeping Open Issues Corrected Monthly	
Sites for the Same Company		
Average Number of Unsafe Housekeeping	Total Number of Fall Protection Issues	
Issues on Other Sites for the Same Company	Corrected Monthly	
Monthly Average Number of Fall Protection	Safe Observations in Month One-Amount of	
Unsafe Observations on Other Sites	Change	
Changes in Total Unsafe Observations in a	Changes in the Average Number of Total	
Month	Inspections Collected in a Month	

 Table 2. Sample of the safety variables considered for testing.

## Developing the loss prediction model

Our research consisted of work completed in multiple phases. The first phase sought to identify individual variables with the highest correlation to loss. The next phase focused on generating the optimum combination of these variables to enable an even more accurate prediction of loss.

We were unable to identify a single variable that strongly predicted future accidents or injuries. In fact, we could not find one variable that had a greater than .30 correlation<sup>3</sup> to loss. See Table 3 for some individual variables that are more correlated to injuries than others. While these single variables may be significant, they were not sufficient or reliable enough as standalone predictors of future accidents and injuries. Like many professionals in the safety industry, we hoped and at one point believed that a single variable like percentage safe or number of inspections could pinpoint sites that are more likely to have a future accident. But given the diversity of observers, management and training systems that abound across a range of sites, the problem is frankly more complex.

<sup>&</sup>lt;sup>3</sup> **Correlation** is the degree to which two or more attributes or measurements on the same group of elements show a tendency to vary together.

Safety Variable	Correlation
Housekeeping unsafe per inspection	.30
Fall protection unsafe per inspection	.23
Unsafe per inspection weekly total	.23
Safe observations per inspection	.22
PPE unsafe per inspection	.22
% of categories inspected	.22
Unsafe per inspection	.20
Number of inspectors	.16
Number of unsafe observations per month	.16
Number of high severity unsafe observations	.15
Number of inspections	.07

#### Table 3. How individual safety variables correlate to loss.

To illustrate this complexity, consider two sites "A" and "B," that each independently increases their inspections by 50%. Site "A" trains its observers on how to do an inspection, involves management in acting on the information and engages employees' participation in deciding what to inspect. On the other hand, Site "B" increases inspections by brute force, mandating a list of what is to be observed, providing little training, and failing to engage leadership or observers to take action on the collected information. Obviously, site "A" will reduce more unsafe behaviors and conditions, particularly in the long run. Grasping the full complexity of the observation environment forced us to look beyond single variables and consider more complex models and combinations of variables that could incorporate these dynamics.

As we continued our research, we discovered that some of these safety variables correlated with each other and speculated that a careful scrutiny of these relationships could present a better indicator of risk. For example, as observers see an increase in unsafe observations, they also see a general increase in unsafe observations for housekeeping. While this not one-to-one, the correlation between some variables (see Table 4), encouraged us to look more closely at the interrelationships among all our variables and to apply a more advanced predictive method for selecting at-risk sites.

Type of Observation/Inspection	Correlation
High Severity Unsafe	.52
Safe	.43
Low Severity Unsafe	.32
Medium Severity Unsafe	.32
Housekeeping	.22

Table 4. How an increase in unsafe observations is correlated to other safety variables.

This method led us to a site scoring system that scored each site from a range of 1 to 1000, with a higher number indicating a greater likelihood of loss and a greater amount of total loss. We developed this system by drawing heavily from the cumulative knowledge and practices of another industry with a vested interest in predicting outcomes—the financial services industry. A pertinent analogy for our site scoring system is the credit score. Most of us understand the fundamentals of how credit scores are calculated. The calculation involves elements such as payment history, time, amount of credit extended and a multitude of other things. In both financial services and safety, we are trying to determine a future outcome based on a person's previous behavior in a specific situation. People's situations—and even behaviors—change over time. But by looking at a pattern of previous behaviors and the groups of individuals which exhibit these behaviors, we can begin to predict the outcome of that group with a much higher level of confidence.

According to our analogy, safety observations are like individual payment history reports. They come from multiple sources and can provide insight on how often safe and unsafe conditions or behaviors are observed, who participated and who did not, and whether participation is increasing or decreasing. Using this approach, we began to test which combination of the thousands of variables we had were really the best indicators of risk. Ultimately, we were able to reduce the number of variables considered from over three thousand to about 400 and could begin to group different types of sites together.

After building 31 different models and undergoing rigorous testing<sup>4</sup>, our most effective and reliable model to date provides the following summary results for scored sites:



Margin of Error - + 4%

#### Exhibit 5. Summary results for our site scoring system.

<sup>&</sup>lt;sup>4</sup> To ensure the accuracy and reliability of our predictive model, we retained an independent consultant with expertise in predictive modeling. By dividing our data sets into multiple groups (one for modeling and one for testing) over multiple time periods we were able to build and test a model for one time period against another data set from a different time period to see if the model was reliable when confronted with real time and change. Models were tested against actual loss information and used randomly selected observations collected from 2005- 2006.

- 92% of all loss occurred on sites with the top third of scores.
- Sites with the bottom two thirds of scores accounted for only 8% of all loss.
- 50% of the sites within the top 10% of high-scoring sites had no accidents.
- 3 out of 4 sites from the top third of scores had no accidents.
- Only 1 in 75 sites within the bottom two thirds of scores had an accident.
- The error rate for the model was plus or minus four percent.

Perhaps the most surprising finding is that only one in four sites in the top third of highscoring sites sustained a single loss. You may have to read that sentence again. Stated another way, a site can appear as though it will have an injury, but for whatever reason, it does not have one. This can partly be explained by the human factor and/or sheer chance. Just because a site could or should have had an accident does not mean it is going to have an accident. The same applies with credit reporting. Just because an individual has had poor payment performance in the past does not mean that he has not learned from the past and corrected his ways. It only means that he fits into a class of customers that on the whole are more risky than others. Of equal interest is the finding that the ratio of sites that would have any injuries at all increased from one in four (when considering the top 33% of high-scoring sites) to one in two (when considering the top 10% of high-scoring sites). Contrast that with the sites with the lowest two third of scores, where only about one in 75 sites have any injuries at all.

The statistical methods employed to calculate this model<sup>5</sup> are beyond the scope of this presentation. However, the following are some general characteristics that are shared by sites with higher scores, which are more at risk for an incident:

- Fewer people participate in the inspection or observation process.
- There are more low and medium severity unsafe behaviors or conditions observed.
- There are more unsafe behaviors associated with housekeeping and fall protection.
- There exists greater variance between safety professionals and non-safety professionals.

# A note on the quality of observations

Throughout this entire process, we wanted to ensure that we had confidence in the observations we were using. You may well be aware—or at the very least suspect—that not all safety observations are equal. Our records included some observations that in isolation are highly suspect. For example, one observer on a construction job site on the Texas-Mexico border recorded 96 inspections in a row without finding *a single unsafe observation*. Professionals in the safety industry are familiar with instances where observation information appears to be manipulated, or pencil-whipped. Initially, we were concerned by the challenge that inaccuracies resulting from pencil whipping might produce, but we decided to turn the situation on its head to see if this suspicious data could be used to help our cause.

<sup>&</sup>lt;sup>5</sup> We used a variant of the rule induction for multivariate regression analysis. Our model currently uses 400 different variables, some of which are referenced in Table 2. For more detailed information on rule induction analysis, please refer to:

Bozdogan, H. Statistical Data Mining and Knowledge Discovery, Knoxville: CRC Press, 2003

To address significant differences in observations, we designed a way to measure the quality of an observation by using safety professionals as a control group. Our assumption is that safety professionals comprise a highly skilled, trained group of observers that is likely to collect consistently high quality, accurate observations. By separating the observations done by safety professionals from those done by non-safety professionals, we were able to calculate their differences by site. In other words, we built into our model a way to identify sites where these two types of observations looked similar and sites where they looked different. So, when a safety professional and a non-safety professional observe a situation in a similar—not disparate—way, we can be more confident in the quality of their observations. Instead of worrying if we could trust these observations, we capitalized on the disparities between them to develop an indicator of potential future risk.

### Recommendations on how to leverage these findings

In general, the more safety and non-safety professionals you have participating in your inspection process, the greater your chances are for preventing an injury. Any extremes in unsafe behaviors should be scrutinized very carefully. Time and again, we found that when organizational norms for observation patterns were exceeded on the high end or the low end, trouble often followed. For instance, if your organization averages 1.5 unsafe observations per inspection, pay careful attention to sites that have consistently higher or lower than 1.5 unsafe observations per inspection. If you track safe observations, watch for a spike in these numbers on a weekly basis. Our research shows that a rise in safe observations oftentimes accompanies a rise in unsafe observations.

When it comes to loss, observations in the housekeeping and fall protection categories require special attention. On the whole, as unsafe observations rise, housekeeping and fall protection unsafe observations increase at a faster rate than any other category. In addition, high numbers of low and medium severity observations are also shown to indicate a general rise in incidents.

In short, you should focus on increasing observers and the quality of their observations, so that more unsafe observations and specifically, more low and medium severity issues are identified. Consider benchmarking your observations and improving the rate at which you resolve open issues. We highly recommend that you set a goal to reduce any gap between inspections done by safety professionals and non-safety professionals. While some variance is expected, we encourage you to establish a baseline for your organization and to immediately address outliers.

Because every organization is different, specific internal goals should be set according to an organization's minimum expectations once it has established a baseline. However, as a starting point, we have provided a few benchmarked averages for the companies that we looked at, for your consideration of minimum expectations:

- 1 inspection per week per observer
- >1.5 unsafe observations per inspection
- .20 housekeeping unsafe observations per inspection
- .13 fall protection unsafe observations per inspection

In the end, the journey to answer the seemingly simple question "can my safety observations help me predict a future incident?" yielded some valuable insight into the relationship between safety observations and loss. Human instinct fuels the desire to predict the future, particularly when it has an immediate impact on well-being. Whether you are the banker looking to extend a loan, or the farmer keeping watch on a looming thunderstorm, you will seek the clues that can help you plan accordingly. Safety observations are the leading indicators that provide you with the precious time to proactively prepare for an incident before it occurs. Unfortunately, like the farmer preparing for the storm, you are the one that has to do the work, bring in the livestock and close up the barn. Nonetheless, it is likely the case that we would all rather have the time to prepare, plan and act at our own pace rather than sprint for the door when the winds are whipping and the wet drops of reality are falling upon us.