Viewpoint

Generating business value from data

Safeguarding reputation and improving efficiency through data-driven risk models

With advances in technology, companies are now collecting far greater quantities of data about their business processes and assets than before. However, existing assurance processes rarely benefit from this data, which limits access to richer insight and may lead to false assurance on performance. There is also the potential for legal implications following an accident, in which a company may be judged to have failed to act on data that indicated an accident was foreseeable. Data-driven modelling approaches better exploit the value of these new sources of disparate data and are readily transferrable into multiple industries, such as utilities, transportation and oil & gas. This viewpoint describes the successful application of this approach in the utility sector, which has led to improved business efficiency by better allocation of limited assurance and operational management resources.

Data usage challenges

Current advances in technology enable companies to capture large volumes of previously unavailable data about their businesses, such as asset conditions and deviations from expected performance by assets or employees. However, the existing assurance processes in some companies often do not exploit these richer sources of data and, as such, can provide a limited or potentially misleading positive report that risks are low. Such data can be overlooked, or seen as too complex to understand or not directly linked to business risk. As such, these remain unused in databases, providing no value.

The collected data is often distributed across multiple databases, with no individual having a holistic view. There is therefore a challenge in turning the data into information to provide insight into the business performance and enable more robust decision-making to improve productivity and risk management. There is further reputational and legal risk, should an accident or other loss event occur: that the business will be perceived as having had access to the data (i.e., knowledge of the precursors of the event), but failed to act upon it in order to prevent the incident ("guilty knowledge"). Such foreseeability can be a pivotal argument in prosecutions. Using multiple databases also creates inevitable consistency issues. One database might show employee productivity, while another shows driving telematics data for the same group of employees, but employee identification records cannot be cross-referenced. In our experience, this can be a symptom of managers in different functions working in silos, with limited cross-functional engagement across disparate databases.

Development of a data-driven risk model

We have developed a four-step approach for building a data-driven risk model, which accounts for multiple databases and addresses the data challenges raised in this paper. For example, it can reveal inconsistencies between databases, highlighting the value to be gained by operational and support functions working together.

Step 1: **Review available data** from databases across multiple business functions, paying particular attention to that which the assurance function previously overlooked.

Step 2: **Analyze correlations** between data and the undesired acts or events, and unpick components of the data to find parameters with strong predictive ability.

Step 3: **Develop and validate a multi-variable risk model** based on these correlations, rather than a traditional model that uses only two or three sources.

Step 4: Create a set of principles for **adjusting the model** regularly when more data become available. Brief senior management on the model outputs and how they can use it to drive actions that generate benefits such as business-efficiency enhancement and cost reduction.

This is a scalable approach. Modern analytical techniques can encompass practically unlimited amounts of data and data sources.

Application in a utility company

Project background

Our client was the metering business of a large European utility company. It is responsible for replacing and installing hundreds of thousands of gas and electricity meters every year, relying on a limited, sample-based inspection approach to gain assurance that the installed assets are safe for the public.

The client had completed an internal audit of its assurance process and found that the actual defect rate in its meter installations was 11 times higher than what had been indicated by its own assurance activity.

"The assurance process was found to underestimate the defect rate by more than a factor of 10"

Such defects expose people and property to risk. For example, electrical-wiring defects introduced during installation can cause overheating, fire or electrocution, and gas leaks have the potential to lead to serious fires or explosions. Such high-risk (HR) defects may not always be apparent from a visual inspection, and can be present for long periods without any disruption to a customer's supply. This leads to the potential for significant impact on a company's reputation in the event of an incident, due to the residential nature of many locations.

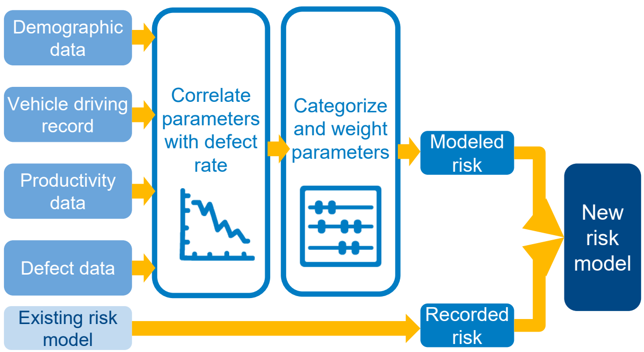
Our diagnostic revealed two key underlying causes of this discrepancy. Firstly, prioritization of inspection activities was not effective, which made it difficult to identify meter technicians (MTs) likely to leave (or who had already left) defects in their work. Secondly, underlying management issues, such as limited cross-functional engagement, were negatively influencing their operational performance.

The underlying causes were addressed by developing a new data model that allowed the company to better prioritize its use of assurance resources and improve business efficiency. The model also provided a better predictive capability than the company's existing assurance regime had to identify both meter technicians who were likely to have already left defects, and those likely to leave defects in the future.

Data-driven risk model development

The four-step approach described above was used to develop the risk model. All available data from different sources across multiple business functions was reviewed, which formed the initial basis for the new risk model. This considered both a "modeled risk" and a "recorded risk" to predict which meter technicians were more likely to leave high-risk defects:

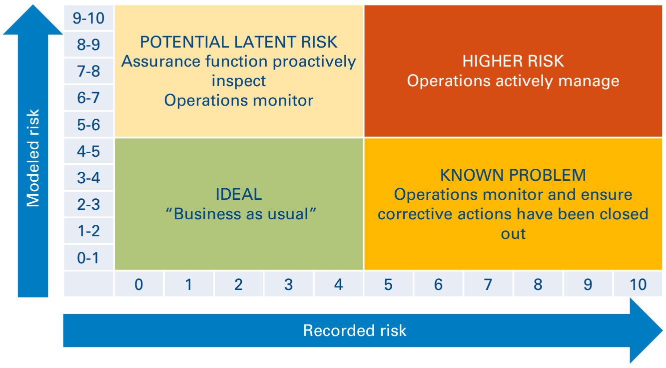
- Recorded risk represents a company's existing risk measure, and is based on observed defects that its assurance function has found.
- The modeled risk relates to a composite measure based on our analysis of factors that have a demonstrable correlation with defect rates.



From the analysis, seven key parameters showed strong predictive ability and demonstrated high levels of correlation with meter technicians who were likely to leave high-risk defects in meter installations.

Strength of correlation	Correlation with high risk defects
High risk defect history	MTs who have left HR defects at any time in the past are more likely to leave them again in the future
Other defect history	MTs who have left lower severity defects at any time in the past are more likely to leave them again in the future
Productivity	MTs who are more productive (i.e. complete more jobs per day on average) are more likely to have left HR defects
Driving history	MTs with more driving risk points are more likely to leave HR defects
Time since starting	MTs are most likely to leave their first HR defect in their first 24 months after leaving the Academy
Driver telematics score	MTs with a lower driving score (based on Trimble data) are more likely to leave HR defects
Geographical regions	Weighting a MTs modeled risk by geographical regions targets regions where HR defects are more likely to be found

Using these parameters, a method for classifying meter technicians based on recorded risk and modeled risk was developed. This was presented as a visual mapping of the risk for every meter technician on a 10-by-11 matrix, split into four main groups that required appropriate line management and assurance focus.



Further development of the risk model followed a three-step process:

- Define high-, moderate- and low-risk boundaries of relative risk for each of the seven parameters.
- Weight these parameters based on the strength of the correlation and their influence on defect rates by assigning values to each parameter – the sum of these gives the modeled risk.
- Test and validate the model.

To define initial risk-category boundaries for each individual parameter, the range of quantitative values was split into low-, moderate- and high-risk categories based on quantiles of meter technicians.

Next, these seven parameters were weighted based on the strength of the correlation and their influence on defect rates by assigning values to moderate and high-risk technicians for each parameter. These weightings were then adjusted using sensitivity analysis to ensure that the new risk model differentiated sufficiently between the technicians with the greatest risk factors, so that the client could focus its assurance and operational management attention where it would provide the greatest benefit.

The effectiveness of the model was validated by comparing the distribution of technicians on the new risk-model matrix who had left defects with that of technicians who had not left defects in the analysis period, under two different scenarios. The two scenarios were analyzed using an independent data set. The results showed that the new risk model was approximately twice as effective as the company's existing assurance process in finding technicians who were likely to leave defects in the future.

Risk-model outcome

The risk model outputs supported more effective and focused management interventions:

- Defining clear responsibilities for both operational and assurance functions to facilitate cooperation in acting on the model's results.
- Focusing monitoring effort on high-risk assets when a business's physical assets are spread across a wide geographic area, making comprehensive assessments or checks impracticable.
- Requesting additional support from operational management for known high-risk assets.
- Increasing monitoring and inspection of physical assets that are at risk of developing unsafe conditions.

Potential application in other industries

The type of model discussed here is relevant to other industries that have asset profiles similar to those in utility companies. For example:

- Assets spread over wide geographic areas in uncontrolled environments (e.g., bridges, earthworks, railway signaling equipment, tank farms and pipeline pump stations).
- Assets with useful lives measured in decades that can go long periods between inspections.
- Assets for which inspections may not consistently detect certain types of latent defects or problems.
- Assets for which the delivery capacity of work is much higher than for the resources available to assure that work has been completed properly.

Such industries also usually have a significant amount of data available on both physical assets and people, which are spread across different departments and often not used to their full effect. This data contains information that could be used to further develop risk-based approaches to either asset inspection or employee/contractor performance. This would be consistent with the move away from time- or sample-based inspection approaches that has occurred in some industries over recent years.

The most applicable areas in similar industries in which this quantitative, data-driven approach can be used are likely to be those for which:

- The nature of the work being completed makes it hard to check (e.g., due to geographic spread or number of assets), and defects are not easily found with a visual inspection.
- Behavioral factors play a large role in the development of unsafe conditions, such as those caused by employees and contractors missing out steps of procedures.
- Work completed is not always checked by third parties, or there is a large element of lone working.
- Good-quality records of assets, employees and contractors are available, even if these are spread across different departments or business functions.

Critical to the success of any risk model is the management arrangements that support its use. Clear responsibility and approaches to managing individuals in each category of risk need to reinforce messages that are in line with a company's overall approach to asset management.

Conclusion

Arthur D. Little developed a data-driven risk model for a utility-sector company, leveraging observable and measurable data from a range of sources and databases to predict high-risk employees and assets. This data-driven approach to risk modeling provides executives with actionable management information that can generate higher business efficiency. The success of the risk model relies on high-quality input data from databases overseen by different departments or business functions, and requires a collaborative approach between individual managers and moving away from operating in discrete silos. The key benefit is enabling increased business efficiency through better use of resources already available to managers, without significant additional expenditure on assurance or inspection activities.

This data-driven approach to risk modeling also has strategic business importance in protecting businesses' reputations. By failing to use such data and its associated insight, companies may be unable to prevent asset failures. Any avoidable incidents that endanger lives of employees and/or the public can cost a business more than replacing a member of staff. It might also involve fines, reduce sales and profits, and generate negative public opinion that is hard to reverse or irreversible. It takes time to recover from such events, but it is relatively easy to prevent damage to business reputation by implementing an effective risk-control model and program.

The model has direct applicability to multiple industries with infrastructure assets, including utilities, transport, and oil & gas. These sectors share many common properties, such as large, geographically dispersed asset bases, and assets installed and maintained by lone workers. With our experience in strategic business management and risk modeling, we can help you to develop a customized risk model that safeguards your business reputation and improves your business efficiency.

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Arthur D. Little

Arthur D. Little has been at the forefront of innovation since 1886. We are an acknowledged thought leader in linking strategy, innovation and transformation in technology-intensive and converging industries. We navigate our clients through changing business ecosystems to uncover new growth opportunities. We enable our clients to build innovation capabilities and transform their organizations.

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